DEMENTIA-INCLUSIVE DESIGN

Machine-Learning Assessment Tool for Evaluating Indoor Wayfinding Quality in Dementia Care Spaces

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Master of Science in Architecture, Urbanism, and Building Sciences

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Dementia Inclusive Design

Machine-Learning Assessment Tool for Evaluating Indoor Wayfinding Quality in Dementia Care Spaces

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Abstract

The design of residential care facilities for individuals with dementia profoundly impacts their quality of life and wellbeing. Dementia-friendly architecture, thoroughly reviewed in literature, provides guidelines and assessment tools to evaluate residential spaces and enhance living conditions. Key to residents' wellbeing is their autonomy and control over their environment, which can be facilitated by optimizing wayfinding within indoor spaces. Effective spatial layouts, particularly those offering good visual access, not only promote autonomy but also improves social integration by enabling residents to see and be seen by others.

This MSc thesis investigates the feasibility of artificial intelligence (AI) to support the design of dementia-friendly architecture, focusing particularly on wayfinding—a critical element of environmental design for individuals with dementia. The study quantitatively assesses the relationship between floor plan layouts and wayfinding ease using the isovist method, linking floor plan geometry with the navigational experiences of dementia patients. The assessment was done in accordance with an established Dementia Design Principles (DDP) environmental assessment tool recognized within universal design guidelines.

A computational framework was developed to evaluate wayfinding quality using visual access analysis, which were integrated into a machine learning model. This model was trained on a dataset of 256 floor plans, employing features derived from two distinct sources: spatial metrics such as distances and centrality from the Swiss Dwellings dataset, and compactness and distance-based features extracted via Grasshopper, a visual scripting tool in Rhino 3D. The model was tested using two supervised machine learning algorithms—Random Forest (RF) and Artificial Neural Networks (ANN)—and achieved consistent accuracy rates between 70-80% using 14 features and 2 multiclass outputs describing the visual access quality. This demonstrates AI's potential as a decision-support tool in the early stages of architectural design, offering architects insights into the wayfinding quality of their designs.

The goal of this research is to develop a digital framework that can be leveraged by architects to link early-stage concept design ideation to the specialist validation of final designs to help guide the design of layouts towards DDP-compliance and reduce risk of design changes, ultimately designs that are easier to navigate by people living with dementia and enhance the quality of living.

Keywords: Dementia-friendly architecture, artificial intelligence in design, indoor wayfinding, machine learning assessment, dementia care spaces, architectural technology, user-centered design, spatial analysis, AI-driven tools in architecture.

Contents

Preface

This report is the result of the graduation project from the Master of Science in Architecture, Urbanism, and Building Sciences at the Technical University of Delft following the Building Technology program from 2022 to 2024. The thesis project was kicked off on 1 November 2023 and concluded on 4 July 2024.

I am very grateful for my peers, the support network, and broadly the Building Technology as a program to investigate topics in the built environment from a technological lens. The past two years have been a very enriching experience, as it was inspirational to be surrounded by passionate researchers and scientists in the field working on exciting topics that before joining this program, I thought were science fiction. I am inspired by the discussions I had at TU Delft on the importance of building performance and the soft human element in our built environment which laid the foundation for defining my thesis topic that tackled computational challenges by bridging design priorities with social needs.

I would like to extend my sincerest gratitude towards my mentors, Dr. Michela Turrin and Dr. Martijn Lugten, for guiding me and pointing me in the right direction. A special thanks to Ir. Lisa-Marie Meuller for her exceptional ability to critically reflect on my progress from the very beginning of the thesis all the way to the end. I am especially grateful for the enthusiasm of external advisors for their interest in my thesis development and providing critical feedback and positive reinforcement that helped shape the process and outcome of this thesis project. I especially thank Dr. Nadja Gaudillière-Jami for dedicating the time to critically reflect on my research, provide references, and guidance throughout the entire thesis project's timeline on all things related to AI. And I especially thank the enthusiasm of experts in universal design and elderly care, Dr. AnneMarie Eijkelenboom for sharing references and reflecting on my topic. And I am grateful for Dr. Birgit Jurgenhake for contextualizing my topic on dementia care environments from an architectural perspective at the early stages of my research which helped shape the direction of my focus.

The participation of Tangram in the beginning of my thesis was the most influential part of my topic definition. Tangram's project plan provided critical questions on the applicability of AI and the soft human value. I am grateful for the participation of Tangram Architecture and for involving me in their exhibition efforts, special thanks to Bart for introducing the topic to the Chair of Design Informatics. Thanks to all Tangram staff for making our collaboration extremely effortless and smooth, Lejla Duran, Anna Lugard, Bas Weststrate, and the exhibition co-contributors for enriching my thesis experience through the planning and execution of the exhibition Immeasurably Important 'Onmetelijk belangrijk'.

Vision Statement

The vision for this project is to leverage the power of artificial intelligence to transform the way we design care spaces for people with dementia. artificial intelligence as a design-support tool has the potential to empower architects and designers to create environments that prioritize the unique needs and preferences of individuals living with dementia, fostering a sense of autonomy, belonging, and wellbeing. Integrating artificial intelligence into the design process can ultimately help with the process of creating inclusive, supportive, and human-centered spaces that enhances the quality of life for a vulnerable user group.

I believe the research presented in this thesis is only the first step towards realizing this vision, and I am excited to continue exploring the potential of artificial intelligence in the field of specialized care environments.

Glossary of Terms

General Terms

Acoustic Wayfinding Cues:
Sounds used to help individuals navigate and orient themselves within a space, particularly useful for people with visual impairments or cognitive challenges.

Behavioral and Psychological Symptoms of Dementia
Symptoms including agitation, depression, anxiety, psychosis, aggression, and sleep disturbances that commonly occur in people with dementia.

Caregiver:
An individual, often a family member or trained professional, who provides care and support to someone with dementia.

Clinical Nursing Homes (TNH):
Facilities providing comprehensive care and medical supervision for individuals with significant health challenges, including dementia.

Cognitive Decline:
A reduction in cognitive abilities such as memory, decision-making, and problem-solving, commonly associated with aging and dementia.

Delirium:
An acute, often sudden, change in mental status marked by confusion, disorientation, and difficulty with attention and memory, which can coexist with dementia.

Dementia:
A neurodegenerative disease typically associated with memory loss and diminished ability to perform daily tasks independently. It is progressive and largely irreversible but can be moderately controlled with medication.

Dementia Design Principles (DDP):
Guidelines for designing environments that accommodate the cognitive and sensory challenges faced by people living with dementia.

Dementia-Friendly Architecture:
Architectural principles and designs specifically created to support the needs and enhance the quality of life of individuals with dementia.

Dementia Stages:
The progression of dementia typically categorized into early, middle, and late stages, each with distinct symptoms and care needs.

Dependency:
The state of relying on others for assistance with daily activities, often increased in individuals with advanced dementia.

End-of-Life Transition:
The phase in care focusing on comfort and quality of life as a person approaches the end of life, often provided in specialized facilities.

Environmental Assessment Tool (EAT):
A framework for reviewing and improving the built environment based on Dementia Design Principles (DDP).

Functional Abilities:
The physical and cognitive capabilities that allow an individual to perform daily activities and tasks.

Livability:
The quality of life experienced in a living environment, including comfort, safety, and accessibility, especially significant for those with cognitive impairments.

Long-Term Care:
A type of care service that supports individuals to meet long-term health or personal care needs, primarily for individuals with chronic illnesses or disabilities, including dementia.

Memory Loss:
A common symptom of dementia characterized by the inability to recall information, events, or experiences.

Navigation:
The act of moving through a space or environment.

Neurodegenerative Disease:
A disorder characterized by the progressive loss of nerve cells, which can lead to conditions like dementia.

Psychological Needs:
The emotional and mental health requirements of individuals, crucial in designing supportive environments for those with dementia.

Quality of Life:
The general well-being of individuals, encompassing physical, psychological, and social aspects of their lives.

Sensory Challenges:
Difficulties related to processing sensory information, such as vision, hearing, and touch, which can affect individuals with dementia.

Sensory Impairment:
Deficits in the ability to receive and process sensory information, including vision, hearing, taste, touch, and smell, which are common in dementia.

Social Integration:
The degree to which individuals feel connected and engaged with their community, important for the mental health of people with dementia.

Spatial Awareness:
Understanding and perception of the spatial environment, crucial for effective wayfinding and navigation.

Special Care Unit (SPU):
A dedicated area or facility specifically designed to provide care for individuals with dementia, focusing on creating a supportive and therapeutic environment.

Stimulation Levels:
The amount of sensory input in an environment, which needs to be balanced to avoid overstimulation or under-stimulation for individuals with dementia.

Universal Design Guidelines:
Guidelines aimed at creating environments accessible and usable by all people, including those with dementia, their families, and caregivers.

Visual Access:
The degree to which spaces are visible from different points within the environment, aiding in navigation and wayfinding.

Wayfinding:
The process or activity of determining and following a path or route between an origin and a destination.

Wellbeing:
The overall state of health and happiness, encompassing physical, emotional, and social aspects, and a key focus in dementia care design.

Artificial Intelligence Terminologies

Activation Function:
Functions like sigmoid, tanh, rectified linear unit (ReLU), and softmax used in neural networks to capture non-linear features.

Algorithm:
A process or set of rules followed by a computer in problem-solving operations.

Artificial Intelligence (AI):
The use or study of computer systems that have some of the qualities that the human brain has, such as the ability to solve problems and learn from data supplied to them.

Artificial Neural Networks (ANN):
A computing system inspired by the biological neural networks that constitute animal brains.

Bin Thresholds:
Values that define the boundaries for binning continuous data into discrete intervals.

Confusion Matrix:
A table used to describe the performance of a classification model by comparing predicted and actual values.

Decision Tree Classifier:
A model used to go from observations about an item to conclusions about its target value.

Feature:
An individual measurable property of a phenomenon, usually numeric or categorical.

Feature Importance:
A technique used in machine learning to determine the importance of different features in predicting the target variable.
Feature Importance Ranking:
Ordering features based on their importance scores to understand their contribution to the model's predictions.
Feature Selection Method:
Methods like Wrapper-based Feature Selection (WFS) and Filter Feature Ranking (FFR) used to select important features for the model.
F1 Score:
The harmonic mean of precision and recall, used to measure a model's accuracy.
GridSearchCV:
An exhaustive search over specified parameter values for an estimator, performing cross-validation to find the optimal parameters.
Hamming Loss:
A metric used to evaluate the performance of multi-label classification models.
Histogram Graph:
A graphical representation of the distribution of numerical data.
Hyperparameter:
Variables set before training a machine learning model that control the learning process..
Hyperparameter Search Methods:
Methods such as GridSearch and Randomized Search to optimize hyperparameters.
Isovist:
A visibility measure used in architectural and spatial analysis to understand the visual accessibility of spaces.
K-folds [or folds]:
A cross-validation method where the data is divided into 'k' subsets, and the model is trained and validated 'k' times, each time using a different subset as the validation set.
Machine Learning (ML):
a subset of AI that is concerned with the development of statistical algorithm that can learn from data and generalize to unseen data to perform tasks without explicit instructions.
Multi-Output Classifier:
A classifier capable of predicting multiple output variables for each input sample.
Neural Network Model Hyperparameters:
Variables like learning rate, number of epochs, and number of hidden layers, tuned to improve model performance.
Pair Plot Graph:
A grid of scatter plots used to visualize pairwise relationships between variables in a dataset.
Precision:
The ratio of true positive predictions to the total number of positive predictions, used to measure the accuracy of positive predictions..
Random Forest Classifier:
A machine learning method based on constructing multiple decision trees during training and outputting the mode of the classes for classification tasks.
Sequential Feature Selector:
A feature selection method that adds or removes features sequentially based on their performance to find the optimal subset.
Supervised Learning:
A type of machine learning where the model is trained on labeled data, meaning each training example is paired with an output label.
Surrogate Model:
A model used to approximate complex real-world processes, often used in optimization problems.
Subset Accuracy:
The fraction of correctly predicted subsets of labels in multi-label classification.
Wrapper-Based Feature Selection:
A method of selecting features by evaluating the model performance with different subsets of features.

Early-Design Soft Design Criteria

Accessibility:
The design characteristic that ensures important amenities are within easy reach and clearly visible, enhancing independent wayfinding.

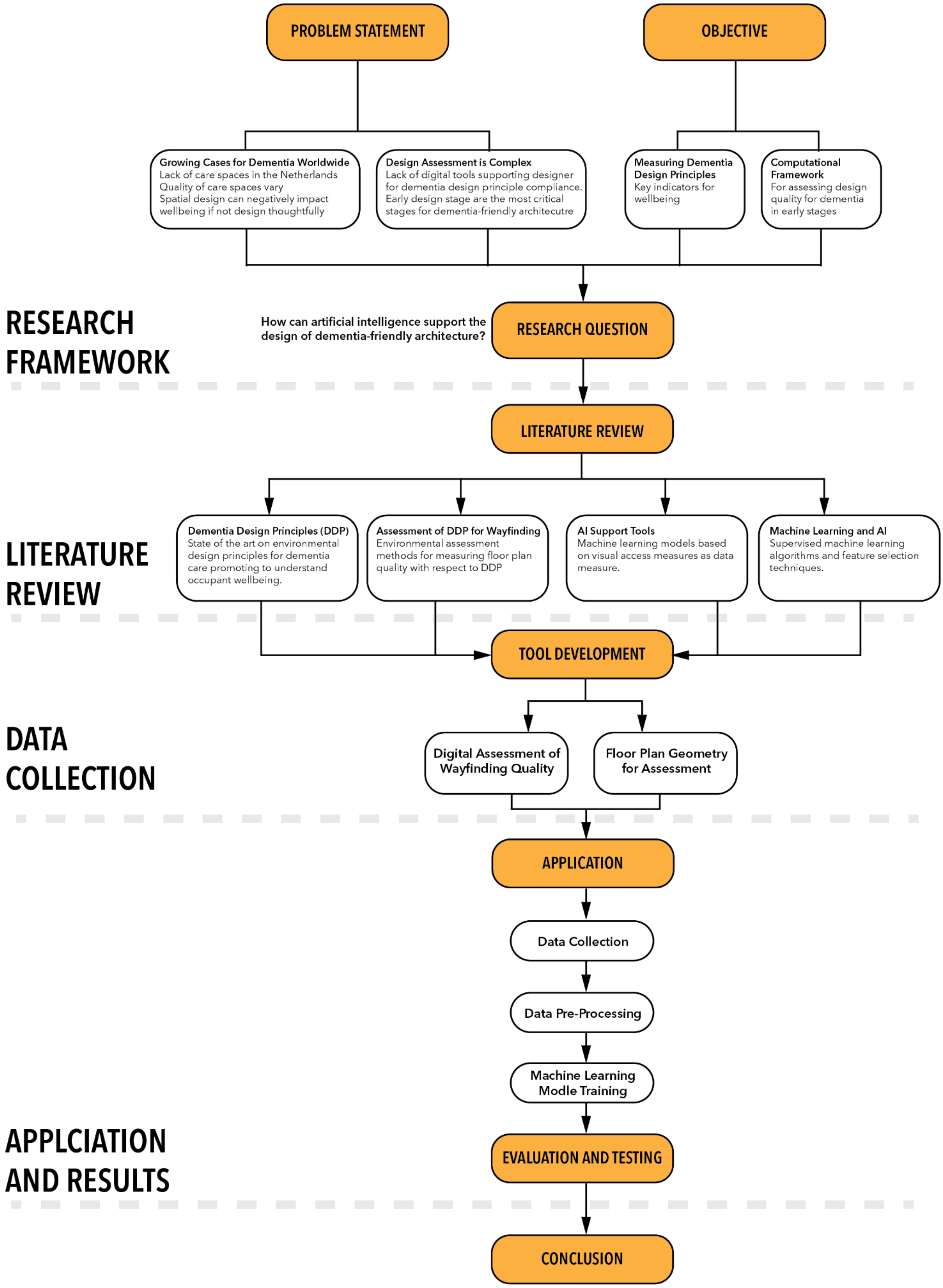
Balanced Stimulation:
The design principle involving the careful management of acoustic and visual stimuli to prevent over- or under-stimulation in the environment.

Personal Autonomy:
The capacity for an individual to act intentionally and make decisions about their environment and movements within it.

Sense of Community:
Spaces designed to enable users to see and interact with each other, fostering social integration.

1 Introduction

methodology scheme



1.1 Background

Dementia is a neurodegenerative disease typically associated with memory loss and diminished ability to perform daily tasks independently. It is progressive in nature and largely irreversible but could be moderately controlled with medication. According to the World's Health Organization, dementia is the leading cause for disability and dependency among older demographics globally (the World Health Organization, 2023). At its core, dementia challenges the very essence of personal identity and autonomy which results in difficulties maintaining normal daily activities required for a high quality of life (Fuchs, 2020). As a result, living with dementia will have major implications on a person's ability to maintain the same quality of life due to psychological, physical, sensory, and overall cognitive decline (Söylemez et al., 2020), traditionally having to live at a nursing home that serve as end-of-life transition in clinical setting with medical supervision and support to mitigate the downsides of dementia. Living in traditional nursing home can run the risk of suffering from an unhealthy living environment especially when it lacks the adequate infrastructure to engage, stimulate, and fulfill their social and psychological needs while also accommodating their new cognitive and sensory challenges because the physical environment can significantly influence independence and wellbeing for people living with dementia (Quirke et al., 2023). Many studies explore the concept of dementia-friendly architecture, most commonly referred to as Dementia Design Principle (DDP), acknowledging the critical role that well-designed environments can help in mitigating the negative effects of living with dementia.

Dementia has become an increasingly bigger phenomenon as the global population tend to have greater number of older people who are prone to developing dementia. The Dutch National Dementia Strategy 2021-2030 estimates the population of people living with dementia in the Netherlands is projected to be over 520,000 individuals by 2050 which is nearly double of estimated figure from 2021 at 280,000 individuals. This also translates to higher care needs and costs increasing from €6.6 billion a year in 2015 to € 15.6 billion a year in 2040 (Ministry of Health, Welfare, and Sport, 2020). In this fifth chapter of the national strategy, titled *Tailor-made support when living with dementia*, it is mentioned that indeed the Netherlands enjoys with having the highest quality of dementia care but acknowledging that there is always room for improvement and that broadly the practical implementation has been lagging, research must find practical application more quickly, effectively, and easily.

> *"Via the task force, we want to encourage the relevant partners to take into account the specific needs of persons with dementia and their families and/or loved ones with regard to residential space, care, well-being, and livability."*
> *-National Dementia Strategy 2021-2030 (Dutch Ministry of Health, Welfare, and Sport, 2020)*

The built environment plays a significant role in boosting quality of life for people living with dementia. It is one of the many contributing factors towards high quality tailor-made support, which is often expensive and difficult to change. The design of care spaces should therefore be rigorously assessed and examined before proceeding to build more care spaces, ensuring the best practices of dementia care standards are validated and followed while building designs are still in the early stages of development.

Preliminary literature review showed that there is a research gap for architectural decision-support tools for dementia care design principles that focuses on qualitative spatial design criteria. In the broader context of design research, the AI-enabled tools for decision-making is an active area of research but have limited applications for supporting architects in early design stages related to designing dementia-friendly architecture.

1.2 Problem Statement

Assessing soft design criteria for dementia-friendly spaces is a complex, multi-variable problem with many decision points that can influence the health and wellbeing outcome for a very vulnerable user group. There is an ever-greater need to directly respond to the unique user requirements through a human-centered design approach that can be measured and validated. The design of dementia residential facilities require deep understanding on how spatial designs could potentially provide the infrastructure needed to empower its occupants to live a fulfilling life. The design process is also multi-disciplinary in nature, and the architect is expected to manage a complex team of specialists and orchestrate a building design that satisfies all the prerequisites for high-quality living, sometimes without being able to involve experts in the field of dementia care design during the conceptual design phase.

During early stages of design, such as *RIBA's Stage 3: Spatial Coordination*, the architect is expected to test and validate architectural concept designs to make sure they are within budget, regulation requirements, client requirements, fire safety, health and safety, and sustainability (RIBA 2020 Plan of Work). In general terms, the effectiveness of a decision decreases as the project progresses along its timeline (Işeri, 2022). Interdisciplinary design teams undertaking conceptual design tasks have been shown to spend the most time in early stages generating solutions and evaluation of choice alternatives (Steele et al., 1999).

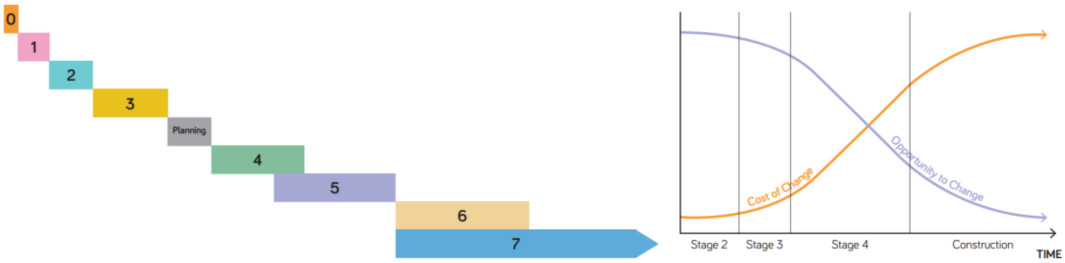


Figure 1: the opportunity for changing decisions decrease overtime while increasing the cost of changes (RIBA 2020 Plan of Work)

The architectural design process vary in their timelines and how long an architect spends in the early stages before proceeding with a design proposal for detailed development. However, it is not always feasible for the architect to extend this phase either to budgetary constraints or lack of available consultants to join an interdisciplinary design team to weigh in on the spatial design at that early stage.

The already constrained and demanding design process is exacerbated by the need to have to quickly build new care facilities in the Netherlands. According to Cushman & Wakefield, one of the largest global commercial real estate services firms, there is a mismatch between the supply for care facility compared to the demand in the Netherlands that can be met by increasing available beds by 35 thousand by 2030, citing the expected increase of dependency ratio of elderly as the main culprit. According to an estimate found online on Statista.com (Statista, 2023), there are around 4900 nursing home in the Netherlands as of 2022, and Cushman & Wakefield estimates 94% of them are operated by nonprofits composing around 116 thousand available beds, making the average size of a nursing home at 24 bed per nursing home. This increase in demand roughly translates to building over 1450 new nursing homes from 2020 to 2030 to meet the demand forecasted in 2019. They conclude by stating nonprofit operators will need to revitalize their existing nursing homes and expand with new properties which foreign investment can fill that gap as traditional ways of financing prove to be insufficient. (Cushman & Wakefield, 2020)

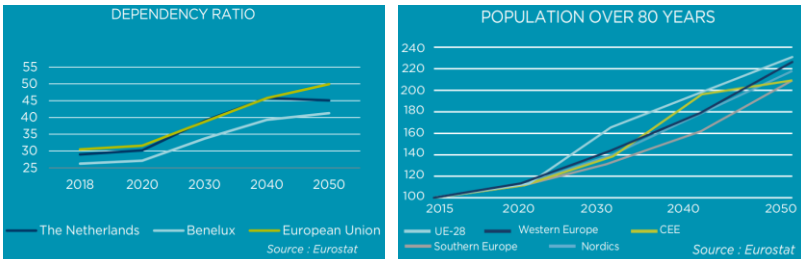


Figure 2: figures published in the report by Cushman & Wakefield, showing an increasing demand for elderly care facilities

With this expected boom in new projects within the Netherlands alone, and considering the complexity of the design of high-quality spaces, there is an ever-growing need for better methods to improve the design process for developing new dementia care facilities without substantially increasing project timelines or cost. It is also worth mentioning that dementia is a global phenomenon and the task for increasing the supply of care facilities is ever more important considering that in anecdotal evidence such as journalistic reporting of personal accounts show that people might be willing to relocate to countries with better care facilities, indicating that the need for high quality care facilities might also be a global need rather than only specific to the Netherlands (Julian, 2023).

This poses the question of how we can rapidly create living conditions that provide high quality of life and encourage a more positive outlook for the health and wellbeing of people living with dementia. This thesis will investigate a data-driven design approach that computationally evaluates the soft design criteria of wellbeing from floor plan geometry with respect to occupant needs living in residential dementia care spaces to support the architect's design decisions during the early stages.

1.3 Research Question

Artificial intelligence (AI) has the potential to support the early stages of design to make informed decisions backed by data. Dementia-friendly architecture and artificial intelligence are both broad terms, we need to ask the right questions on what exactly the aspects of dementia-friendly architecture are the most critical to address in early stages of design, and how can AI support the decision-making process during the design solution stage and evaluating design alternatives.

1.3.1 Main question

❖ How can artificial intelligence support the design of dementia-friendly architecture during the early stages?

1.3.2 Research Sub-Questions

- What are the essential qualitative spatial design features that promote wellbeing for people living with dementia?
  A comprehensive literature review on the current state-of-the-art for all things related to the design of dementia care spaces. This is to discover the thesis main focal point on specific design criteria that are addressed in early stages of design.

- How can digital tools for assessing floor plan geometry be implemented to measure ease of wayfinding based on dementia design principles?

After determining the main focal point, i.e. *wayfinding*, we then ask the question of how we measure qualitative aspects computationally to better describe the wayfinding quality of indoor environments.

- What are the prerequisite data needed to build a machine learning model that predicts the wayfinding quality from floor plan design representation?
  This is to answer the question of what we actually need to start building a machine learning model that is able to predict the wayfinding quality of indoor environments with respect to dementia design principles.

- To what extent can a machine learning model predict wayfinding quality from floor plan information?
  Once the prerequisite data is determined, the question then becomes what machine learning algorithms, features, and model architectures perform best for predicting the wayfinding quality of indoor environments.

- In what way can the AI model be deployed in the design process?
  This question is to investigate how AI can be integrated in the workflow of architects.

1.4 Research Aim and Methodology

The aim of the research is to develop an AI-driven methodology for building machine learning models that have potential benefits for supporting the architect's decision-making process during the early stages of the design of residential care facilities. Particularly investigating the possibility of a tool that can analyze floor plan information and provide feedback in the form of qualitative assessment describing the performance of a floor plan layout using early stage design criteria based on dementia design principles. The inspiration behind this thesis was built upon a project plan document by Tangram Architecture posing the question of how AI in architecture can interpret the non-measurable side of design such as happiness, wellbeing, social cohesion, and beauty (Appendix 1) to which I gladly accepted the challenge without knowing exactly was ahead.

With that in mind, the research has formulated the following objectives:
1. Investigate the state-of-the-art review of the design of dementia care facilities, and in parallel investigate AI-enabled tools that might be relevant to the research question.
2. Define wellbeing in this thesis by selecting a specific user group and building typology, and propose a method for measuring it.
3. Develop a computational framework for generating and/or obtaining data through Grasshopper software package for the purpose of training the AI model.
4. Develop the code environments on programming language, Python, for handling the data and experimenting with different AI models through machine learning libraries such as SKLearn and TensorFlow.
5. Evaluate the performance of the model with validation and test sets.

1.5 Research Relevance

1.5.1 Scientific Relevance

The thesis relevant to the field of building technology by investigating a topic on AI-driven methodology for assessing wayfinding quality in dementia care spaces. It bridges a gap in architectural decision-support tools focused on qualitative spatial design criteria, particularly for dementia care.

1.5.2 Societal Relevance

The tool developed has the potential to enhance the quality of life for individuals living with dementia by improving the design of care facilities that will be designed and built in the future. It addresses a growing need for dementia-friendly environments as the population ages, which is crucial for public health and welfare while aligning with the Dutch National Dementia Strategy 2021-2030, emphasizing the importance of high-quality, tailored support for individuals with dementia. This thesis project underscores the role of well-designed environments in supporting the wellbeing of a vulnerable group, and bridging the gap between DDP expertise and design process in the early stages through AI.

2 Literature Review

The scope of the literature was intended to review state-of-the-art dementia design care guidelines while also identifying AI-enabled support tools that are developed for assessment of design spaces for dementia-friendly criteria. There was a gap in the AI-support tools that address dementia-inclusive design, in particular, no tools were discovered that assessed ease of wayfinding of floor layouts with respect to dementia design requirements. However, there were research done that implemented AI to identify the visual connectivity of spaces or used perception-based analytical methods for training an AI model to classify the function of spaces (i.e. private or public).

The most relevant AI tool discovered to have potential in being applied for dementia-inclusive design was published by Foster + Partners (Tarabishy et al. 2020) with developing a surrogate model approach for assessing spatial and visual connectivity to support the design process of office space layouts. The model they have developed can produce visual connectivity maps by inputting a floor plan layout and outputs the floor plan with a heat map. Their model was trained on 6000 floor plans and produced noteworthy results. The discovery of this study led to further investigation for AI tools that uses visual connection analysis methods as training input, but to specifically classify the quality of spaces with respect to dementia-inclusive soft design criteria. There were no AI tools discovered to assess the quality of residential or care facilities with respect to wayfinding.

A challenge for planners and architects to designing dementia-sensitive environments is the that the multitude of indoor, and outdoor, dementia assessment tools makes it difficult for non-researcher to identify exactly which studies are methodologically sound, i.e. in relation to simple geometry, to translate research insights into practice (Kuliga et al., 2021). A study by Quirke et al. (2021) developed a framework for evaluating floor plans with respect to the dementia design principles categories commonly referred to in dementia care literature. They demonstrated a methodology for evaluating floor plans using qualitative queries to populate a checklist and rank floor plans based on their qualitative performance. The discovery of this study led to further examination of the dementia design principles and an attempt to bridge the gap between qualitative assessment of dementia-inclusive design and AI-enabled performance assessment tools.

Therefore, there was a clear gap for AI-enabled tools that are designed to assess the qualitative performance of floor plans with respect to human-centric design criteria such as dementia design principles in order to support the architect's decision-making process during the early stages of design.

2.1 Understanding Occupant Wellbeing

The definition of Wellbeing in the English language, based on the Oxford English Language dictionary, *is the state of being healthy, happy, or prosperous*. Understanding the physical conditions for which an occupant feels in a state of comfort has been researched well which addresses the aspects of indoor environmental quality conditions. For example, empirical studies established very precise acceptable temperature ranges and recommended daylight levels, the most commonly used reference being ASHRAE (The American Society of Heating, Refrigerating and Air-Conditioning Engineers) establishing comfortable ranges based on the studies done previously, which is published in a manual containing standards for thermal environmental conditions for human occupancy where it defines thermal comfort and comfort zones (American Society of Heating, Refrigerating and Air-Conditioning Engineers, 2020)

In building design and engineering, health and comfort have a defined boundary. A healthy building reduce the likelihood of disease and infection, for example by reducing the spread of airborne viral infection by increasing ventilation rates through mechanical or passive means (Urschel et al., 2022). Comfort Have a slightly fuzzier boundary where what is considered comfortable varies from person to person which could include physiological traits and personal preferences affecting how the same environment might be perceived comfortable for one person but uncomfortable to the other. In this instance, it is useful to use comfort ranges, for example, comfortable indoor temperature ranges based on the expected level of activity and outdoor climate conditions. In the case of prosperity and wellbeing, it is usually defined depending on the type of study and the specific user behavior observed in these environments (Zhang et al., 2012).

There are several wellbeing quantification methods for the built environment; for example, the WELL Building Standard® is a performance-based system that considers quality indicator of physical environment, such as air quality, light, and water, and combines it with lifestyle indicators of fitness, nourishment, and mind (International WELL Building Institute, 2020). Another wellbeing-oriented scoring system is the Fitwel® Standard which addresses wellbeing of occupant for different building types (Rider & Van Bakergem, 2022). Their senior housing category has listed multiple criteria such as daylight access, acoustic comfort, and air quality; however, it lacks the consideration of potential cognitive decline of occupants and how might spatial design can better accommodate its users' special needs.

A more relevant guideline document specifically made for understanding the needs of users living with dementia has been published in 2015 titled the *Universal Design Guidelines: Dementia Friendly Dwellings for People with Dementia, their Families and Carers* by the Centre of Excellence in Universal Design (Grey et al., 2015). In this document, it goes further to explain the design of the built environment to specifically improve the living conditions for all people but especially those who suffer from dementia. In their executive summary, it's stated that these guidelines should enable people living with dementia to have the choice to live for as long as possible in their own homes and communities by making dwellings friendlier towards them. The literature review conducted in this master thesis confirm that these design guidelines, when are sufficiently met, have a high likelihood of increasing the quality of life for people with dementia.

Architecture plays a significant role in the health and demeanor of people living with dementia. Depending on the severity of dementia, some individuals require care and supervision in specialized care facilities. There is a direct correlation between health outcome and housing situation, indoor environments in particular (Quirke et al., 2023).

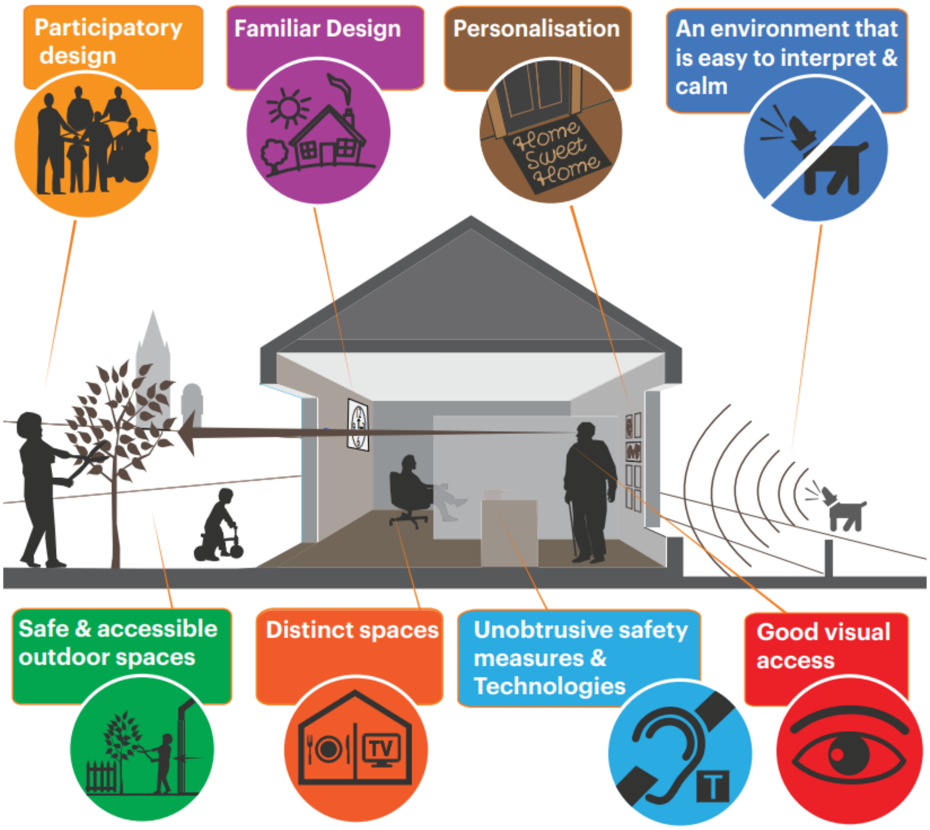


Figure 3: The spectrum of categorical design guidelines to create friendlier living environments for people with dementia. Source: Universal Design Guidelines Dementia Friendly Dwellings for People with Dementia, their Families and Carers (Grey et al., 2015).

2.1.1 Clinical Nursing Homes and Residential Care Communities

The literature suggests that there are two most common care facilities: traditional nursing homes (TNH) and small-scale homelike special care units (SCU). The study showed that overall, there was positive effects to living in homelike SCU setting has positive effects on behavioral and psychological symptoms of patients with dementia (Kok et al., 2016) although the authors of those studies stated that this topic is scarcely investigated and "cautiously" suggest that homelike SCU are more favorable in some aspects of cognitive domains but urges more research on this subject to provide further evidence.

Another peer-reviewed study suggests that SCU provide more social integration than TNH (Abbott et al., 2017). Dementia SCU are designed to facilitate a supportive social environment as well as what's known as a prosthetic environment. A prosthetic environment is a space that can compensate for limitations in functional abilities to enable individuals to "carry out basic activities associated with daily living safely and independently, participate in social roles, and receive personal assistance from caregivers as needed" (Olson, 2010). There are more studies revealing benefits of living in SCUs, specifically, it was found to be "positively associated with several long-term care quality indicators, including less frequent tube feeding, less user of physical restraints, lower risk of pressure ulcers, better continence care, fewer behavioral disturbances, and lower risk of hospitalization, and higher quality of life" (Cadigan et al., 2013).

While the comparison of TNH and SCU are still being researched, most evidence so far suggests that there are merits to SCUs which warrants further investigation within the architectural design domain in pursuit of restorative and supportive built environment for people living with dementia.

2.1.2 Unique User Requirements and Dementia Design Principles

The designs of SCU for individuals living with dementia necessitate consideration of unique user requirements. Dementia introduces distinct challenges, encompassing sensory impairments in vision, hearing, sight, smell, and spatial awareness. Thereby, designers should pay particular attention to spatial design features that can accommodate the occupant's unique needs. Spatial design criteria are examined in a series of papers looking into how layouts can support wayfinding skills for people with dementia. The most recent and detailed studies have been selected after searching scientific paper databases such as Google Scholar and Scopus.

Van Hoof conducted a literature review and qualitative study on how someone living with dementia perceives their environment. The author defined dementia sensory perception as a condition characterized by an "impaired identification of incoming stimuli (perceptual deficits), resulting in distorted perceptions" (Van Hoof et al., 2010). This study is the beginning of standardization of building services and engineering requirements for supportive indoor environments specifically for dementia residential spaces.

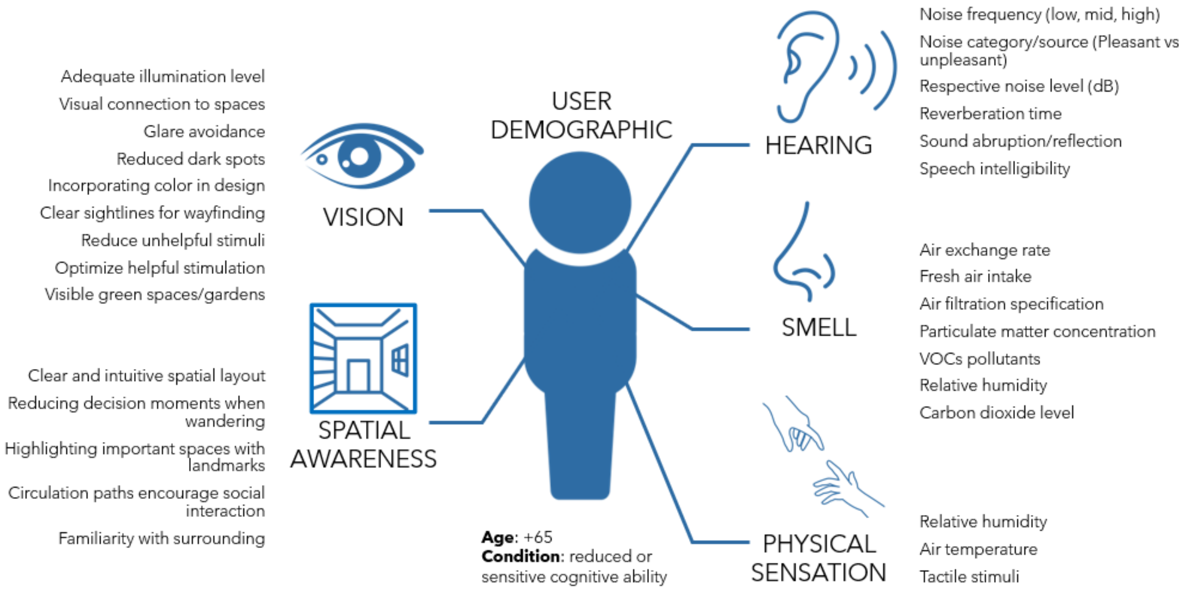


Figure 4: sensory-based design and engineering considerations for occupants with dementia.

2.1.3 Hearing

People living with dementia are particularly vulnerable to confusion, agitation, and illusions caused by unregulated noise. While it is not always the case that people with dementia have hearing loss, the ability to interpret what is heard accurately becomes challenging (Hayne & Fleming, 2014). One of the studies mention the two most critical engineering requirements for sound parameters are sound pressure and reverberation time which are critical for creating supportive environments (Van Hoof et al., 2010). The ability to hear normal conversations is usually not affected unless there is background noise that is difficult for dementia patients to filter out. A recent study found the impairment in the ability to filter out white noise from conversation could be a factor that has a strong correlation with dementia (University of Oxford, 2021). Van Hoof's study recommends limiting noise levels and reverberation time, especially limiting noise from mechanical ventilation systems in tight spaces such as bathrooms that might cause undesired effects on the health of the patient.

Beyond engineering requirements, there is a field of study that investigate the perceived quality of sound, known as soundscape design. Soundscape studies are exploring the domain of acoustic spatial environments and their perception by specific user groups. Soundscape studies are showing that the diversity, quality, and prominence of sound played a role in the quality of life of occupants in nursing homes (Francesco et al., 2017) (Talebzadeh et al., 2023). More research investigate the potential of using sound art as therapy for people with Alzheimer's disease (Sabran et al., 2018). Soundscape environments in nursing homes are often suboptimal (Kosters et al., 2022) that can be a barrier for attaining high quality of life when simple, so called, "micro-interventions" to the nursing home's sonic environment could reap substantial benefit on the health and wellbeing of the occupants. These findings warrant further research into this topic.

The literature review included studies that investigated the role of everyday sounds, providing pre-recorded user-specific sound profiles from everyday activities has shown to be beneficial for evoking memories and emotional responses in advanced dementia care which also revealed that it stimulated "meaningful conversation, playfulness, and connection between residents and caregiver" (Houben et al. 2020) which necessitates further examination and studies on how everyday sounds from indoors sounds affect user behavior in a community residential setting. In particular interest, a vibrant dementia village living community for example. The same study mentions everyday sounds help occupants cope better, "help to build an understanding of the environment and provide information on how we physically and socially negotiate it" (Houben et al. 2020). A systematic review of (Janus et al. 2021) showed that apathy might be linked to the environmental stimuli especially related to sound intensity exceeding 50 dBA causing issues like annoyance, disturbed sleep, delirium, and elevation of blood pressure. Moreover, another study suggest that the environmental stimuli that intended to prompt or encourage the participant's reaction might have a negative correlation with apathy among dementia patients, in addition to stimulation clarity and strength (Jao et al. 2015).

2.1.4 Spatial Awareness and Wayfinding

The criterion of spatial awareness is explored in many recent studies specifically investigating how indoor environments can support independent living and preserve the person's autonomy when living in a dementia care facility, something that has been positively correlated with increased quality of life and overall perceived wellbeing. Research on spatial wayfinding is abundant and provides a good starting point for architects to develop designs of dementia SCUs.

The most comprehensive spatial layout study was conducted by Marquardt investigating the relationship between floor plan layout against 14 dementia design criteria noting that spatial disorientation is a prime reason for institutionalization (Marquardt & Schmieg, 2009). One way to improve spatial orientation is to provide fewer decision moments along path of travel, unique and memorable reference points, commonly referred to as landmarks, with clear visibility to along the path of travel and from/to important spaces (van Buuren & Mohammadi, 2022). Van Buuren highlights that properly designing paths of travel has the potential to empower people living with dementia at an SCU in finding their way around, thereby reclaiming some of their autonomy, and urges architects to examine the design criteria presented in their study, specifically corridor length, width, shape, moment of decisions, and daylight access. Moreover, visual access between key spaces mentioned in the 14 design criteria (van Buuren & Mohammadi, 2022).

Some examples of relevant criterion to spatial awareness:

Criteria 4: Visual access between entrance hall and living room

Criteria 5: Visual access between living room and corridor
Criteria 6: Visual access between individual room and sanitary room

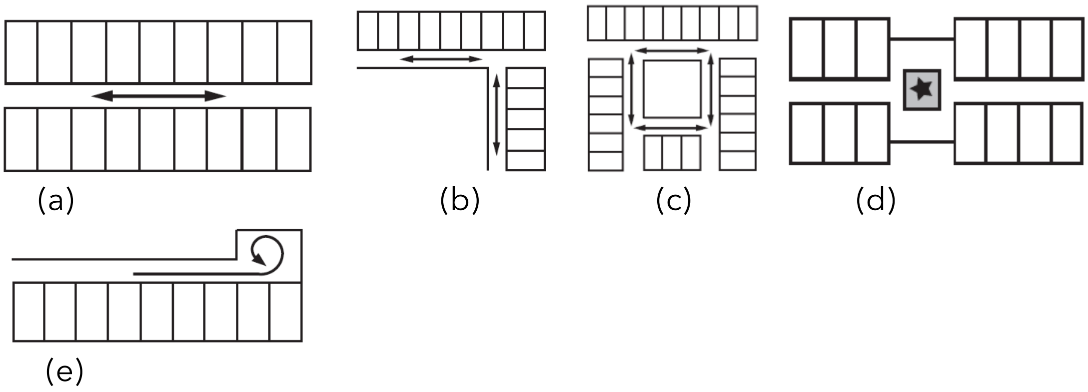


Figure 5: Exploring different spatial organization using different corridor shapes. (a) linear, (b) L-shape, (c) circular, (d) intermediate element dividing corridor, (d) corridor ending. (Marquardt & Schmieg, 2009) Note the use of landmarks to divide corridors are considered desirable, and more straightforward corridor shape with fewer turns is also considered more desirable.

Additional wayfinding criteria highlighted in the literature was added in Appendix 2 and Appendix 3.

2.1.5 Smell

The elderly have a more difficult time distinguishing between smells and decreased protection from noxious odors caused by age-related losses in olfactory and tastebuds. Moreover, van Hoof also adds that familiar homelike smells and fresh air from the outdoors can serve as olfactory cues that serve as orientation aid and some studies claim that smells help improve wayfinding skills among dementia patients, for example, locating the kitchen via cooking smells

2.1.6 Vision

Van Hoof noted age-related vision deterioration results into impaired ability to adapt to changes in light levels, higher sensitivity to glare, reduced visual acuity, restricted field of vision and perception, reduced contrast sensitivity, and restricted color recognition.

2.2 Quantifying Dementia Design Principles

2.2.1 Evaluation of Floor Layouts

The topic of physical environment and long-term care for people living with dementia has been examined around 2010 by Prof. Richard Fleming which set the foundation for one of the most common environmental design guidelines (Fleming & Purandare, 2010). This evolved later on by Fleming and Bennett (Fleming et al., 2017) to provide design principles for dementia care design and Environmental Assessment Tool (EAT) checklist that provides the necessary framework to evaluate spatial design based on the DDP they established. A dementia design principle (DDP) is a term used in describing a quality within the built environment that enhances the wellbeing and quality of life of an individual living with dementia. The key DDPs were published in several articles, co-authored by Professor Richard Fleming, a psychologist and environmental design expert, and Kristy Bennett, a consulting architect specializing in DDPs. The document was later adapted into a user-friendly handbook. According to the official document, the EAT is a systematic framework for reviewing the built environment to identify areas for improvement with respect to compliance with the DDPs. They go into describing the requirements needed to satisfy each DDP. These requirements were a major source of inspiration for developing the assessment indicators. One of the key aspects that differentiate this study is that it address the topic of cognitive stimulation for people living with dementia, noting that maintaining optimal amount of stimulation is required for healthy living, including both auditory and visual stimuli. Moreover, it puts emphasis on social cohesion, security, human scale, and provisions for wandering, something that was not discussed in the earlier study by Marquardt and Schmieg (2009).

A different study applied these principles for the evaluation of floor plan layouts, named Plan-EAT (Quirke et al. 2021), "The paper concludes that the Plan-EAT could benefit architectural practice by providing an evidence-based means of assessing layout planning quality, in both existing cases and emerging residential care facility design proposals". This study has demonstrated a methodology for assessing floor plan layouts based on the EAT checklist that can be leveraged by architects to establish a framework to evaluate to what extent their floor plan follows the DDPs to be used in the design proposal stage. The strength of the methodology is that it comprehensively covers all DDPs from the EAT handbook, providing a broad general assessment of a floor plan's quality with respect to all DDPs.

The checklist for visual access assigns 1 point per criterion, indicating whether it has been satisfied. This qualitative assessment step classifies each sightline criterion as either satisfactory (1) or insufficient (0). The paper does not elaborate on varying degrees of visual access or any quantification measures. However, it suggests that this could be manually assessed through human inspection or via software, which is necessary for a data-driven assessment of the visual access indicator.

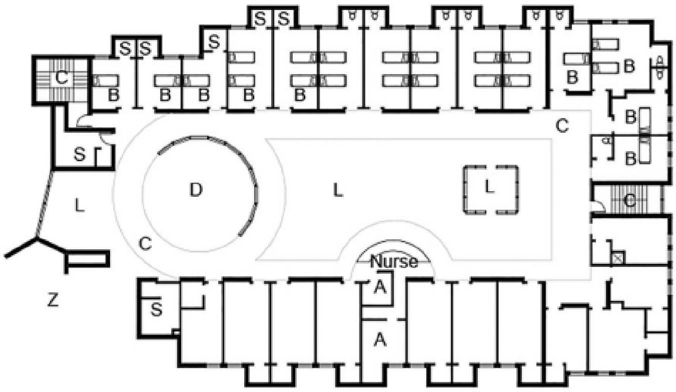


Figure 9. Case 33 – Unit layout.

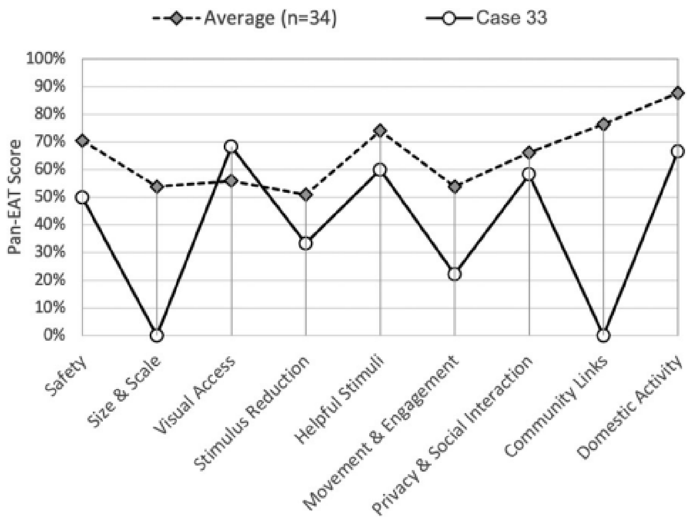


Figure 10. Case 33 – Plan EAT graph.

Figure 6: Plan-EAT assessment graph for floor layouts based on the DDP by Fleming & Bennett (Quirke et al. 2021)

A study titled "Lessons Learned from Three Australian Dementia Support Facilities" (Hing-wah et al. 2018) analyzed the indoor quality to understand the design impact on quality of life and wellbeing of the residents. The three dementia support facilities were assessed for visual access using fieldwork observation, design evaluation, and space syntax analysis (Univresity College London depthmapX, n.d.) which is the hallmark software package for quantifying the visual connectivity of space with one another. The study specifically looked into evidence on how the built environment accommodates its residents living with dementia.

In their assessment, various isovist-based analysis were conducted to measure spatial and social properties of plans to accommodate occupant movement, accessibility, and surveillance ability from staff locations. The isovist analysis responded to the design principle "orientation: direct lines of sight" by examining the line sight measured from the communal kitchen. In their assessment, they concluded facility A performed best due to the sightlines extending deep towards the corridors, whereas in the case of facility C it was more confined due to the location at the corner of the layout. Thereby concluding centrality of the kitchen location has positive correlation with orientation especially considering that the kitchens in these facilities are gathering social spaces. The assessment for orientation had three possible outcomes: best (3 points), better (2 points), good (1 point).

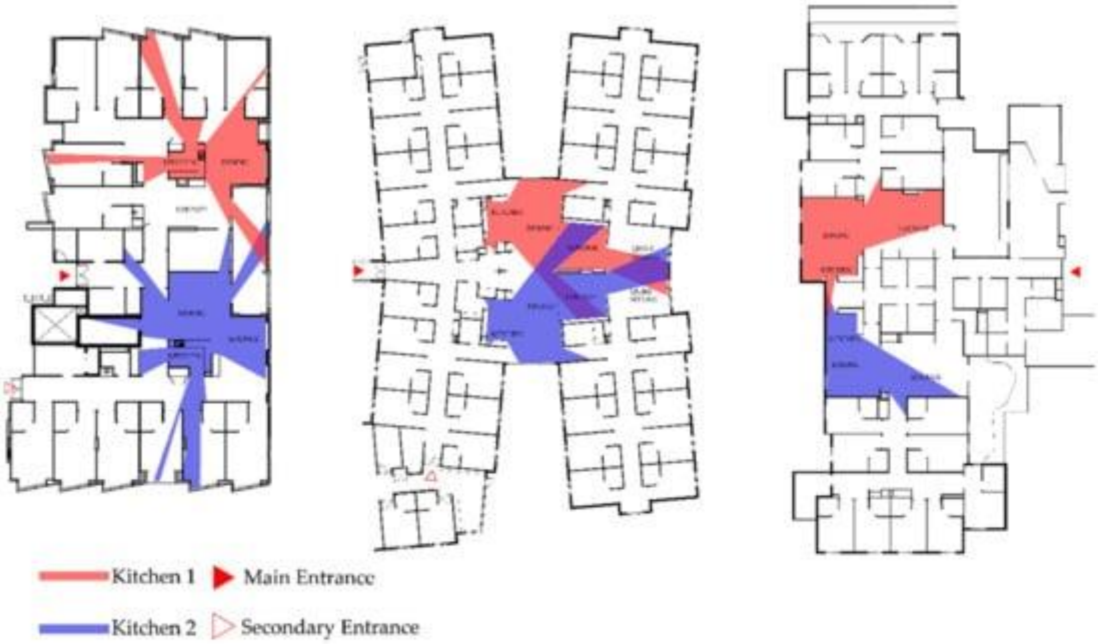


Table 7. Comparison of direct lines of sight.

Design Principles	Facility A	Facility B	Facility C
Orientation: Direct lines of sight	***	**	*

Notes: * = Good; ** = Better; *** = Best.

Figure 7: Isovist analysis was conducted to estimate the visibility of kitchen from staff location for 3 dementia care facilities in Australia. Isovist analysis: Facility A (left), Facility B (middle) & Facility C (right) (Hing-wah et al. 2018)

The evaluation of floor plans using DDP has been demonstrated in the literature as a useful tool for evidence-based design approach. The visual access category has been shown to be assessed computationally using isovist-based analysis to visualize the sightlines and check against the DDP conditions to see to what extent they have been met.

2.3 AI Enabled Support Tools

The literature review included finding AI-enabled assessment tools that used isovist (visual perception measurements) as variables for the training of their model. Some approaches included using isovist values to classify whether a space is likely to be public or private while others used isovist data to produce visualizations to support the design process.

2.3.1 Study A: Supervised Learning – Deep Learning Surrogate Model for Spatial and Visual Connectivity by Tarabishy et al. 2020

A study conducted by Foster + Partners (Tarabishy et al. 2020) investigated the use of supervised machine learning techniques to automatically generate spatial and visual connectivity of floor plans. Their machine learning model is capable of identifying spatial and visual connectivity potential of a space to support the design of workplace layouts. They emphasize setting up the required simulation is difficult depending especially when considering the resolution of the isovists and the sizes of floor plans.

From the perspective of the paper, a surrogate model's main objective is to speed up the analysis process for a specific design task as a replacement for conventional visibility graph analysis simulation for complex projects which are used daily within the design workflow providing real-time results for visual connectivity. Their main argument is that in the early stages of design it is helpful to evaluate floor plan performance for spatial and visual connectivity which designers can use to improve wayfinding and space use. The authors mention this can inform the design of wall partitions and furniture depending on the location of the isovist either at knee level or eye-level [perhaps considering kids and people using wheelchairs].

The end product their designers use is the color map visualization on floor plans where each cell corresponds to the value of spatial and visual connectivity. For spatial connectivity, the colors describes the average shortest distance taken to travel to every other location calculating the graph using Dijkstra's algorithm and shortest path algorithm. For visual connectivity, the colors represent how visually connected the spaces are at a given location [cell] on the grid to all other locations. To calculate that measure, Dijkstra's algorithm is used again to traverse the graph "while the calculations done according to visibility graph analysis as described by Turner et al.'s article."

The analysis is done using an existing simulation engine to calculate both spatial and visual connectivity. The study's main contribution of the authors of this study is the development of "a properly tailored dataset to train a deep learning neural networks and investigations of the appropriate architecture of the neural network itself." They present the parametric creation of floor plans and automatic completion of their respective analyses high-performance computing system to parallelize the simulation process. Ultimately the task is to make the resulting simulation result interpretable by the machine learning algorithm through a supervised learning approach.

The authors use a floor plan input image containing black pixels for walls, and the resulting output is the analyzed floor plan. The color gradient is representative of the analysis result performed is more common for image processing techniques such as style transfer, and colorization is opposed to vision problems such as image segmentation.

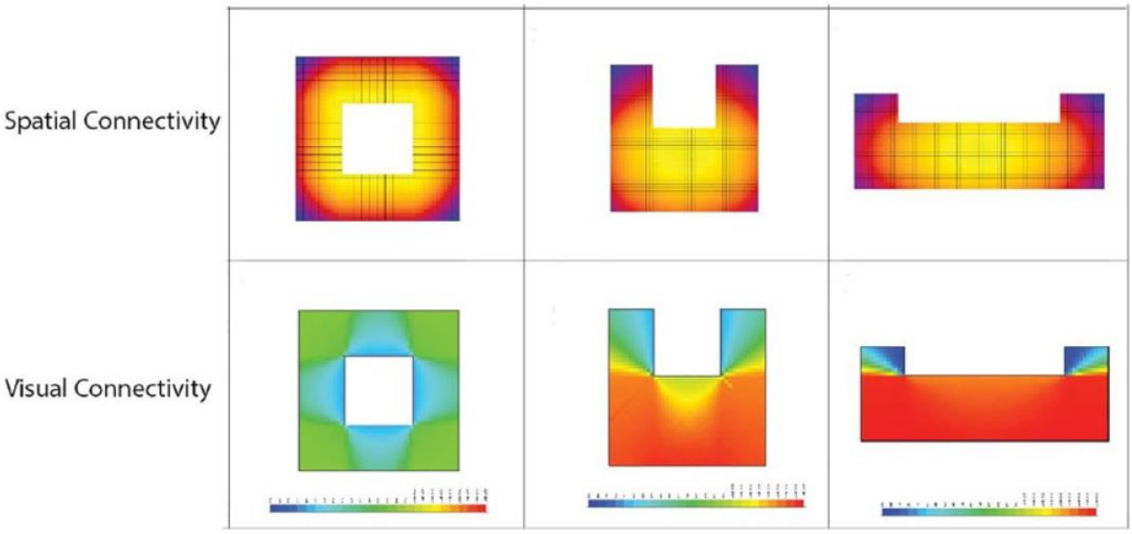


Figure 8: Visual and spatial connectivity analysis (Tarabishy et al. 2020)

Their data acquisition approach through publicly available floor plan images is not the most efficient citing that most often than not publicly available floor plan images contain too much noise and drawn in different styles, so cleaning and pre-processing the data is laborious and time consuming making them unattainable. The authors instead opted to synthetic data generation through Rhino and Grasshopper interface capable of automating the production of 2D floor plans containing different wall and furniture arrangements, thereby creating a plethora of spatial organization. Their test was able to generate 6000 floor plan images of 100 x 100 pixel where each pixel represents 1 m2.

In addition, the author generated a signed distance function (SDF) for all floor plans, a technique commonly used in computer vision for simultaneous localization and mapping (SLAM) algorithms [e.g. three-dimensional reconstruction using depth cameras]. "The SDF is expected to encode local geometry details along with the global scene structure." The authors also used on-the-fly augmentation to randomly flip some floor plans vertically or horizontally to avoid memorization and overfitting. The output (post-analysis dataset) contained 100 x 100 pixel images with every pixel remapped to gray scale 0 to 255 based on the analysis results.

For the choice of neural network architecture, the intent was to pick an option that is scalable and offer good localization and manage to propagate context information throughout the whole model. The two choices were between fully convolutional network (FCN) and U-Net network. The contracting part is a typical convolutional neural network (CNN) made of successive down-sampling operation blocks successively applied on top of each other with the first applied to the input image. The author state that the objective is to "ensure that the network effectively learns complex structures and features." Operational blocks consists of two 3 x 3 convolutional layer, followed by a 2 x 2 max pooling operation to reduce the dimensionality of the input while increasing the number of extracted features.

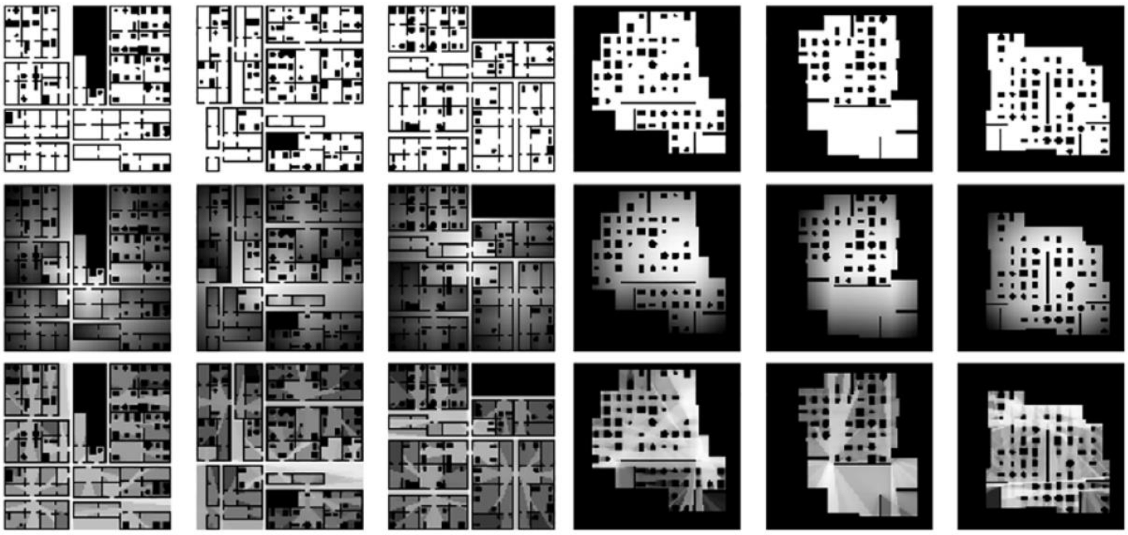


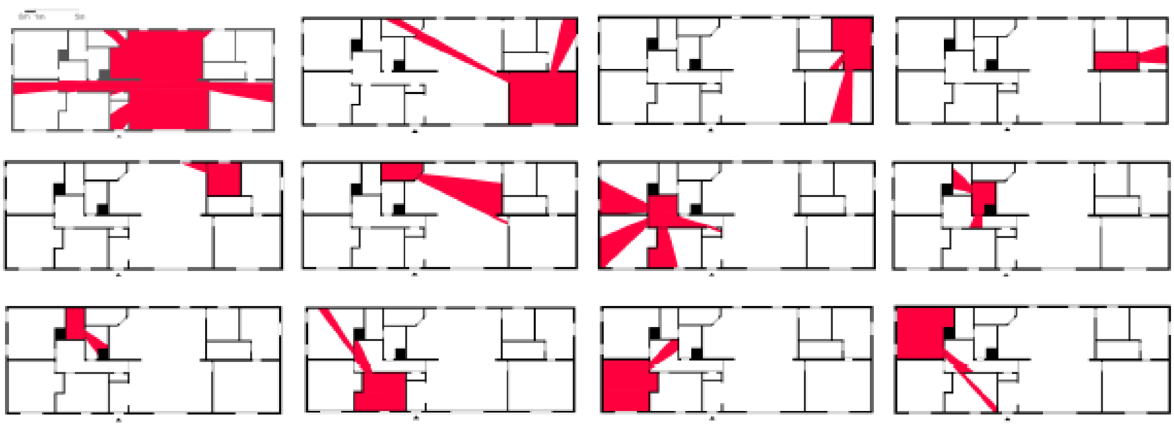
Figure 9: The first row represents the binary dataset as produced by the generative process. The second row represents spatial connectivity (0-255), the third row represents visual connectivity (0-255) (Tarabishy et al. 2020)

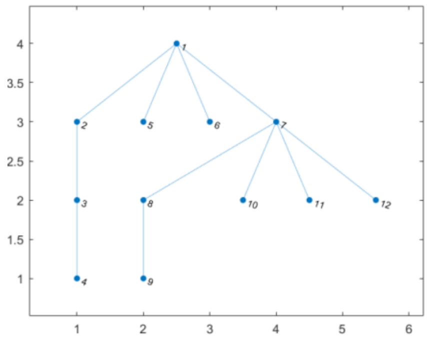
2.3.2 Study B: Supervised Learning – Towards a Machine Learning for Space Syntax by Ferrando 2018

A master thesis dissertation from Carnegie Mellon University that explores the idea of a machine learning algorithm that learns from a database of vernacular architecture to understand the spatial quality from floor plan layouts. One of the [many] questions posed in this research is how can we train a deep neural network for the classification of spaces based on their isovists? One of the foundational studies that inspired Ferrando's work was "Machine Perception of Space" by Peng which was a master thesis proposal from MIT that used isovists to explore the relationship between geometry and spatial awareness.

Ferrando's contribution was to apply the methodology to a specific room function classification problem by training a neural network to evaluate a floor plan and assign a privacy label on rooms where it is appropriate based on the training from a dataset of French farmhouses according to their isovists and graphical representation. The data allows for a machine learning model to understand the characteristics of a space and predict a suitable function for different rooms in a floor plan where the target variable is level of privacy from 0 and 1.

Their data acquisition approach was to collect floor plan data in raster format, vectorize the plan using corner detection algorithm (Harris Corner Detection) to vectorize the walls which then allows for running the isovist simulation for all rooms. The isovist sampling was done on Python 3.6 environment then extracted the numerical values used for the training. The centered isovist calculates the visible floor area from the isovist vantage point.





Sample	Room	Room Area	Total Floor Area	Room to Total Area	Centered Isovist	Centered Isovist to Room Floor	Centered Isovist to Total Floor	Number of visual neighbors	Function	Privacy	Degree Centrality	Betweenness Centrality
1	Room 1	79.6	222.1	0.358	122	1.53	0.55	6	Living	0	4	37
1	Room 2	28.0	222.1	0.126	40.9	1.46	0.18	3	Bedroom	1	2	18
1	Room 3	14.7	222.1	0.066	21	1.43	0.09	2	Bathroom	1	2	10
1	Room 4	6.2	222.1	0.028	9.5	1.53	0.04	1	Closet	1	1	0
1	Room 5	8.7	222.1	0.039	9.8	1.13	0.04	1	Laundry	0.5	1	0
1	Room 6	5.4	222.1	0.024	21.4	3.96	0.10	1	Storage	0	1	0
1	Room 7	11.9	222.1	0.054	32.5	2.73	0.15	4	Distribution	0	5	39
1	Room 8	5.1	222.1	0.023	8	1.57	0.04	2	Dressing	0.5	2	10
1	Room 9	4.7	222.1	0.021	6.5	1.38	0.03	1	Bathroom	1	1	0
1	Room 10	15.3	222.1	0.069	19.9	1.30	0.09	2	Bedroom	1	1	0
1	Room 11	21.2	222.1	0.095	24.2	1.14	0.11	1	Bedroom	1	1	0
1	Room 12	21.3	222.1	0.096	25.3	1.19	0.11	2	Bedroom	1	1	0

Figure 10: Dataset sample. Each isovist is taken at the geometric center of each room and tabulated into this spread along with the level of privacy expected. (Ferrando 2018)

Model	0 Class Accuracy	1 Class Accuracy
Nearest Neighbors	78.57 % (11 / 14)	53.33 % (8 / 15)
Nearest Neighbors (Scaled)	78.57 % (11 / 14)	46.67 % (7 / 15)
Nearest Neighbors (Optimized)	78.57 % (11 / 14)	60.0 % (9 / 15)
SVM	78.57 % (11 / 14)	53.33 % (8 / 15)
SVM (Scaled)	71.43 % (10 / 14)	60.0 % (9 / 15)
SVM (Optimized)	78.57 % (11 / 14)	53.33 % (8 / 15)
SVM (RBF Kernel)	92.86 % (13 / 14)	20.0 % (3 / 15)
SVM (RBF Kernel) (Scaled)	78.57 % (11 / 14)	60.0 % (9 / 15)
SVM (RBF Kernel) (Optimized)	92.86 % (13 / 14)	20.0 % (3 / 15)
Logistic Regression	85.71 % (12 / 14)	53.33 % (8 / 15)
Logistic Regression (Scaled)	78.57 % (11 / 14)	46.67 % (7 / 15)
Gradient Boosted Trees	92.86 % (13 / 14)	46.67 % (7 / 15)
Gradient Boosted Trees (Scaled)	85.71 % (12 / 14)	60.0 % (9 / 15)
Gradient Boosted Trees (Optimized)	92.86 % (13 / 14)	46.67 % (7 / 15)
Logistic Regression - L1 Penalty	85.71 % (12 / 14)	53.33 % (8 / 15)
Logistic Regression - L1 Penalty (Scaled)	78.57 % (11 / 14)	46.67 % (7 / 15)
Random Forest	71.43 % (10 / 14)	46.67 % (7 / 15)
Random Forest (Scaled)	92.86 % (13 / 14)	26.67 % (4 / 15)
Random Forest (Optimized)	71.43 % (10 / 14)	46.67 % (7 / 15)

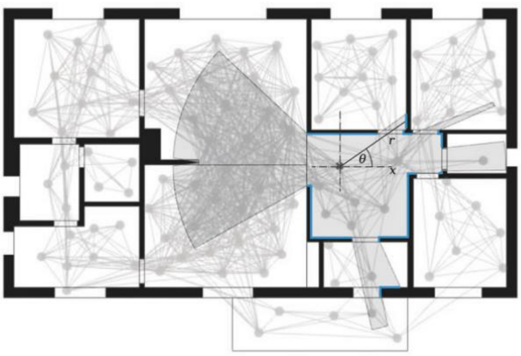
Figure 11: Test results using different algorithms. (Ferrando 2018)

2.3.3 Study C: Unsupervised Learning – Deep Learning Spatial Signatures

A study using isovist values to train an AI model on extracting spatial patterns from isovist analyses which opens up the possibilities for data-driven strategy to measure spatial quality using isovists (Johanes & Huang, 2022). Their methodology can be summarized in 4 steps: (a) isovist sampling on floor plan dataset, (b) GANs training and inversion, (c) latent space interpretation, and (d) architectural decoding shown in the following figures. In this study, they use an isovist periodic function, "that characterize a panoramic view of space" to compare embedded spatial qualities. The floor plan dataset are in SVG format which is processed in Grasshopper to extract the geometry and perform a stochastic isovist sampling for each floor plan.

The authors use GAN inversion technique (Xia et al., 2022) is a technique utilized by the authors of this study to "recover the latent vector of a given input data" allowing the interpretation of GAN's latent space. The encoder did not yield good results and they attribute that to having highly diverse isovist layout. This experiment was done on hundreds of thousands of isovist samples collected from housing floor plan using latent space representation structure of 1d convolutional progressive growing GAN.

The study presents a method for evaluating potential design option by using its isovist signature and compare it to the latent space for regularity [the degree of similarity between isovist signatures in the latent space] and uniqueness [the degree of difference to other isovist signatures in the latent space]. While this in itself does not address wayfinding score, the isovists of floor plan to a typological reading of spatial design by classifying any isovist sample given to the model to see where it exists in the latent space which can be combined helpful for selecting from design options during the early design phase.



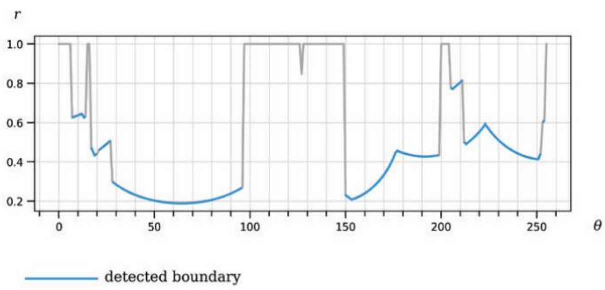


Figure 12: isovist sampling and periodic function (Johanes & Huang, 2021)

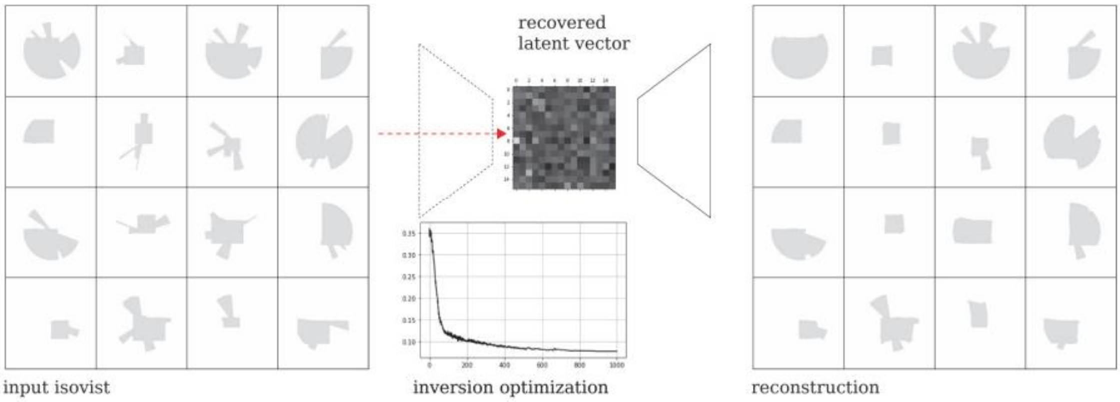


Figure 13: GANs inversion experiment framework (Johanes & Huang, 2022)

2.4 Conclusion

In summary, the literature review highlights the critical gap for AI-enabled support tools built specifically to support the design processes for dementia-friendly architecture, particularly concerning wayfinding. While there has been significant development in AI tools for general spatial analysis and classification, such as those developed by Foster + Partners using surrogate models or visual connectivity, no existing tool effectively address the specific needs of dementia-inclusive design criteria. This gap necessitates the development of specialized AI tools that can evaluate the qualitative aspects of spatial design, focusing on the ease of wayfinding for individuals with dementia. These tools should integrate various design principles, such as visual connectivity, spatial layout configuration, and sensory stimuli to support architects in creating environments that enhance the wellbeing of dementia patients in residential care settings. Future research should continue to explore and expand the capabilities of AI in this domain for dementia-friendly indoor environments, ensuring that the tools developed are robust, user-friendly, and capable of providing actionable insights during the early stages of design where decisions are critical to ensuring compliance with the dementia design principles.

3 Wayfinding Design Criteria

3.1 Principles that Promote Wellbeing

The literature review conducted in this master thesis to understand the full spectrum of influencers for wellbeing has shown that preserving pre-dementia lifestyle is essential for high quality of life for people suffering from dementia, ideally staying in their own homes unless not feasible then it becomes a question of finding a suitable care facility that feels most like home. Moreover, the idea of personal autonomy and being able to exert control over their environment has been shown to increase the sense of home in elderly care facilities which is an essential ingredient for improve health and psychological wellness (Rijnaard et al. 2016) which ensures preservation of occupant's existing habits and values, allowing them to cope better with their condition. Moreover, the same study also emphasizes that social interaction is another ingredient for having a sense of home in elderly care facilities which is facilitated by quasi-public spaces and allocation for private spaces. The studies on care facilities highlight that visual connectivity is among the most important factors for improving wayfinding, thus personal autonomy, as well as a sense of community.

The literature review also uncovered the need for appropriate levels of stimulation to maintain a healthy mind. This has been experimentally tested using customized soundscapes curated for each occupant's preferences, but more importantly, the everyday sounds have a big influence on occupant behavior. The presence or lack of sounds from everyday life affects user behavior, including sounds coming from kitchen, boiling kettle on the stove, chats in the hallways, and subtle music from the lounge, which is also a sentiment shared by practitioners in the field as described by Tangram Architecture's elderly care home Zuidoever which is perceived positively by staff and residents (Robert Muis, 2024). These stimuli have the potential to influence the behavior of occupants in a way that promotes their engagement in their environment as well as anchoring their sense of directionality aided by additional sensory cues such as smell and sound.

Taking into consideration the need to promote personal autonomy, a sense of belonging, and engaging surroundings, the soft design criteria for ideal living conditions have been defined in the next section reflecting these findings from the literature.

3.2 Design Criteria for Describing Perceived Wellbeing

From a design point of view, it is helpful to keep some concepts as goals in the early design stages by using evaluation criteria, such as DDP that promote personal wellbeing. It should therefore be included in the decision-making process when exploring floor layout options. The process of designing floor layout options is often brief, quick, and intuitive which makes it prone for selecting sub-optimal options only to realize that in the schematic or design development phases that it does not adhere to the DDPs. The (soft) design criteria established here is meant to guide the design process in a way to verify whether a design option promotes wellbeing.

The entire spectrum of design criteria are all linked to improved wayfinding quality which is going to be the basis of the measurement. These four qualitative metrics provide a starting point to evaluating design options with user needs in mind. The design criteria were established to better guide the quantification method for dementia-friendly architecture and is still limited to only providing qualitative guidance based on universal design principles. The designer should also consider health and comfort engineering criteria which are as important in the early design phase to control thermal comfort and daylight availability.

3.2.1 Personal Autonomy

The definition of Personal Autonomy in this context is spaces that give the capacity for the individual to act intentionally, be able to make decisions to move in their environment and be able to follow through with them, thereby exerting control over their decision to what parts of the building a user wishes to occupy. The underlying benefit here is the occupant given the choice to engage in their surroundings, to be able to change their settings, move independently from one space to another with minimal chances of confusion or getting lost.

Visual access plays a critical role in giving autonomy to the occupant. However, there are many design features that help improve wayfinding such as the amount of decision moments along a corridor, the number of doors along a corridor, route length between individual bedroom and living, and differentiated corridor using landmarks and niches. All of which improve independent navigation in indoor environments.

3.2.2 Sense of Community

The definition of Sense of Community in this context is spaces that allow the users to be able to inspect different spaces in their environment and see others while also being seen by others. The key to creating a strong sense of community is excellent visual access between spaces. For example, users spending time in the lounge can easily see other adjacent spaces of interest such as the garden or dining room. This can also provide subtle environmental stimulation to prompt and encourage interaction in a natural way. This also has the added benefit of improving wayfinding quality by means of visual access between spaces.

3.2.3 Balanced Stimulation

The definition of Balanced Stimulation in this context is understanding how acoustic and visual stimuli are shaped by the floor layout. The desired level of stimulation present in a home varies from person to person, and understanding how spatial stimuli are perceived can allow for customization of spaces to fit the needs of an individual or living group. The key to having balanced stimuli is to vary the stimulation across floor layout and avoid a concentration of spaces with over or under-stimulated environments. For example, the floor layout provides sufficient separation between vibrant parts of the building to the quieter and more private areas. Acoustic stimulation has been noted in the guidelines and literature to provide added benefit for improving wayfinding by anchoring the occupant's sense of directionality to a stimuli in addition to vision. Visual stimulation is important to consider as well. For example, artwork and murals can provide visual interest and engagement, but should be used thoughtfully to avoid overstimulation. Additionally, the use of color and contrast can help to define spaces and make them easier to navigate.

3.2.4 Accessibility

The definition of Accessibility in this context is important amenities are within reach and clearly visible or easy to find. For instance, visibility to toilets from all common areas will improve independent wayfinding.

3.3 Selection of Performance Indicators for Indoor Wayfinding Quality

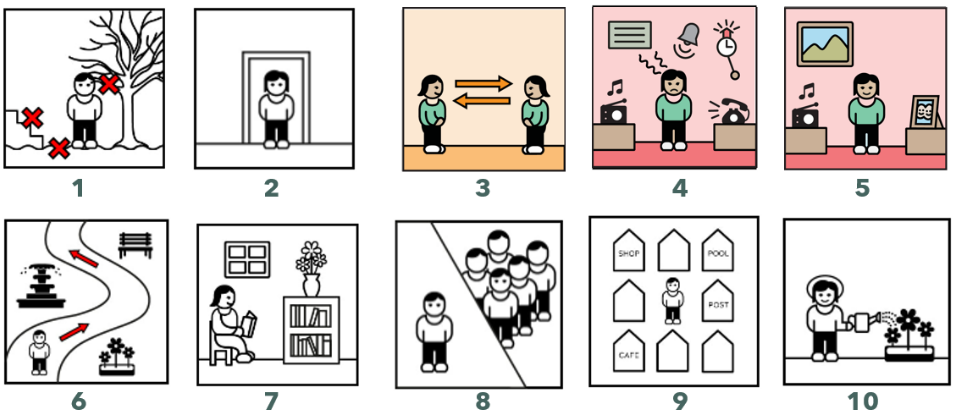
To assess how floor layouts comply with the design criteria, a reliable set of performance indicators needs to be established in order to provide more consistency and control over the assessment. Several performance indicators have been selected based on the EAT that might also support wayfinding abilities of users. These assessment indicators are used to determine whether a floor layout is compliant with the established four soft design criteria.

The majority of indicators are related to visual access. They are conditions to say whether a space or an object is visible from another space. This not only help residents to see and be seen as described in the DDP, but also aid with wayfinding and helps reduce the chances of getting lost while navigating indoor environments. The amount of visual access is intertwined with the building layout including allocation of wall dividers and spatial organizations, both of which are often, if not always, addressed in the early conceptual phases such as *Stage 3 Spatial Coordination in RIBA Plan of Works*. The performance indicators are therefore selected as the basis for the assessment to get a better understanding of the navigational quality of spaces that also by association improve the likelihood of supporting the occupants with better sense of autonomy and community engagement.

The stimulation indicators have been based on reoccurring themes found in the literature. More specifically, how everyday sounds contribute to wellbeing and wayfinding cues (Houben et al. 2020 and Grey et al., 2015). It is useful to understand how spatial design influence the acoustic quality from everyday sounds. It also helps gauge the estimated level of stimuli levels so that low or highly stimulated environments can be discovered for the purpose of customizing environments to suit the individual needs for ideal level of stimulation.

Combining spatial and sound indicators can give us an idea on how likely someone can be independent in their environments which ultimately helps with wayfinding and provide them with the choice to engage in their environments while remaining aware which spaces they wish to occupy, and follow through with their decisions based on the visual and acoustic cues presented to them.

The selected DDPs from the EAT checklist are highlighted in the figure below that have association with improved wayfinding.

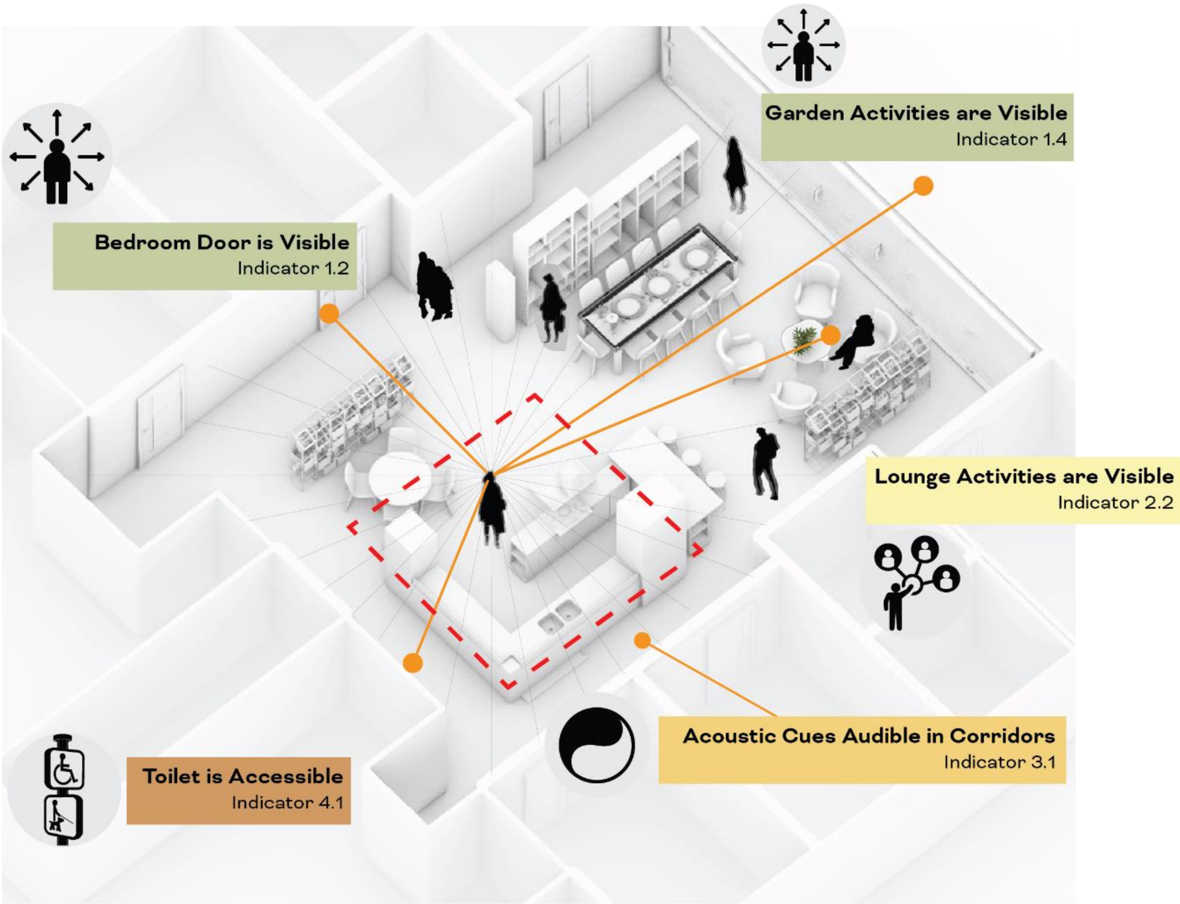


1. Unobtrusively reduce risks
2. Provide a human scale
3. Allow people to see and be seen
4. Reduce unhelpful stimulation
5. Optimize helpful stimulation
6. Support movement and engagement
7. Create a familiar space
8. Provide opportunities to be alone or with others
9. Provide links to the community
10.Respond to a vision for way of life.

Figure 14: out of the 10 dementia design principles, three were highlighted for narrowing down the scope of the study (Fleming & Bennett 2017)

The full document of the EAT checklist and Plan-EAT assessment queries are included in handbook by following the reference PDF link (Fleming & Bennett, 2017).

MEASURING SOFT CRITERIA



MEASURING KITCHEN QUALITY BASED ON ASSESSMENT INDICATORS

Figure 15: Soft criteria are defined by a set of measurement to be taken based on floor plan geometry

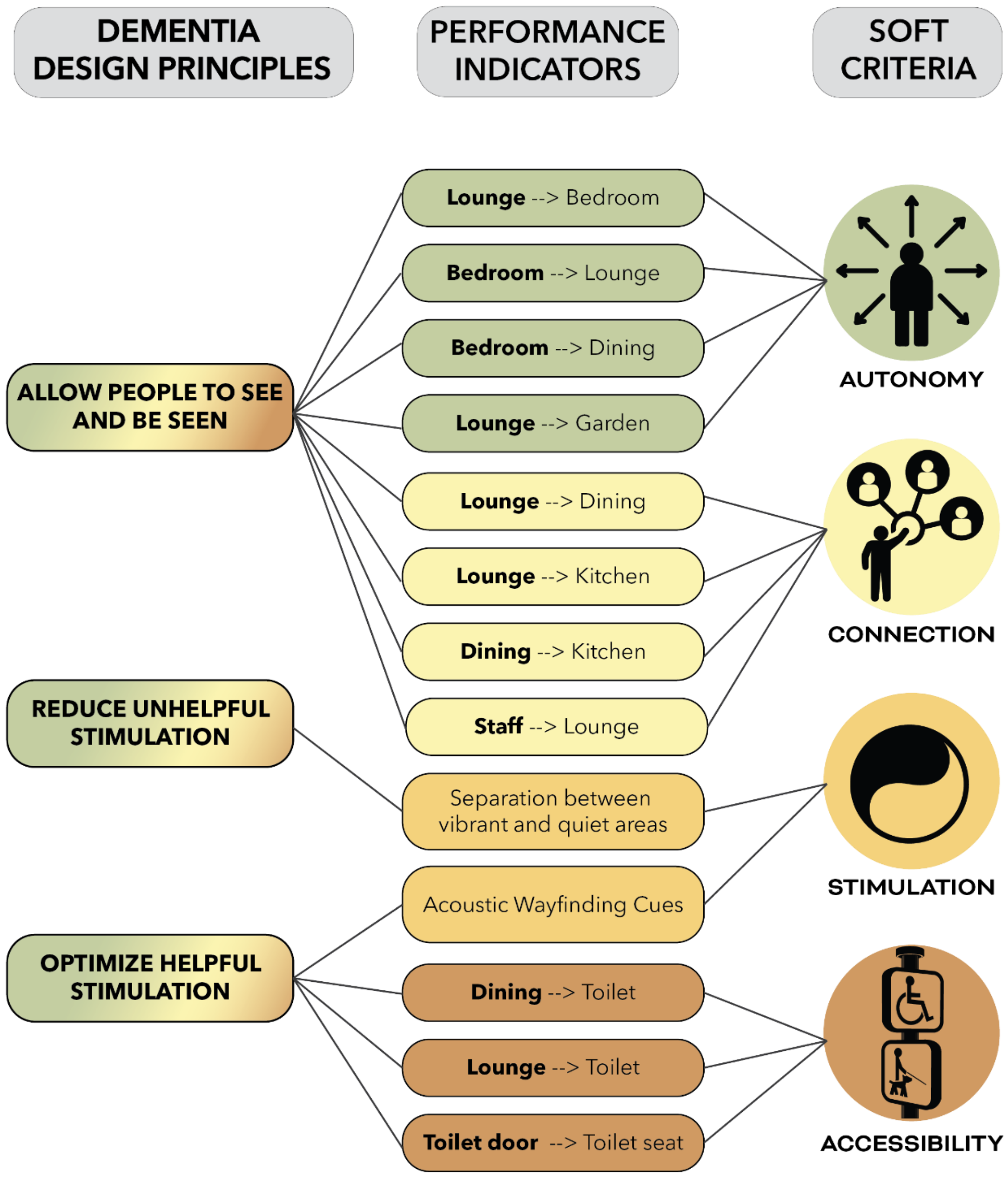


Figure 16: Relating performance indicators to dementia design principles and soft design criteria (Fleming & Bennett 2017)

3.4 Adapting the Dementia Design Principles into a Wayfinding Scoring System

The EAT already has a scoring system where each criterion is a single point which is used as a basis to develop a scoring system specific for wayfinding. The wayfinding performance indicators have been linked to the established soft design criteria to come up with a simple point-base system to determine the degree of compliance for a design criteria. Additionally, the scoring system introduces a range of possible outcomes instead of binary yes/no response by introducing a third possible outcome of "preferred" in order to identify the most suitable design configuration and provide a more granular assessment. The performance indicators can be assessed per room function and by defining the threshold variable for insufficient outcomes, sufficient outcomes, and preferred outcomes in terms of visual access.

3.4.1 Label Assignment Per Room Function

Based on possible scores per design criteria, a label will be given to indicate whether a space fulfils the design criteria or not. Each zone can receive a certain number of labels that relate to each design criteria. The thresholds for satisfying the design criteria is recommended in the scoring schedule in order to give categorical level score that is culminated from wayfinding assessment indicator results. The categorical distinction of design criteria compliance is intended to give overall quality of a floor plan whereas an indicator gives individual assessment of one individual criterion.

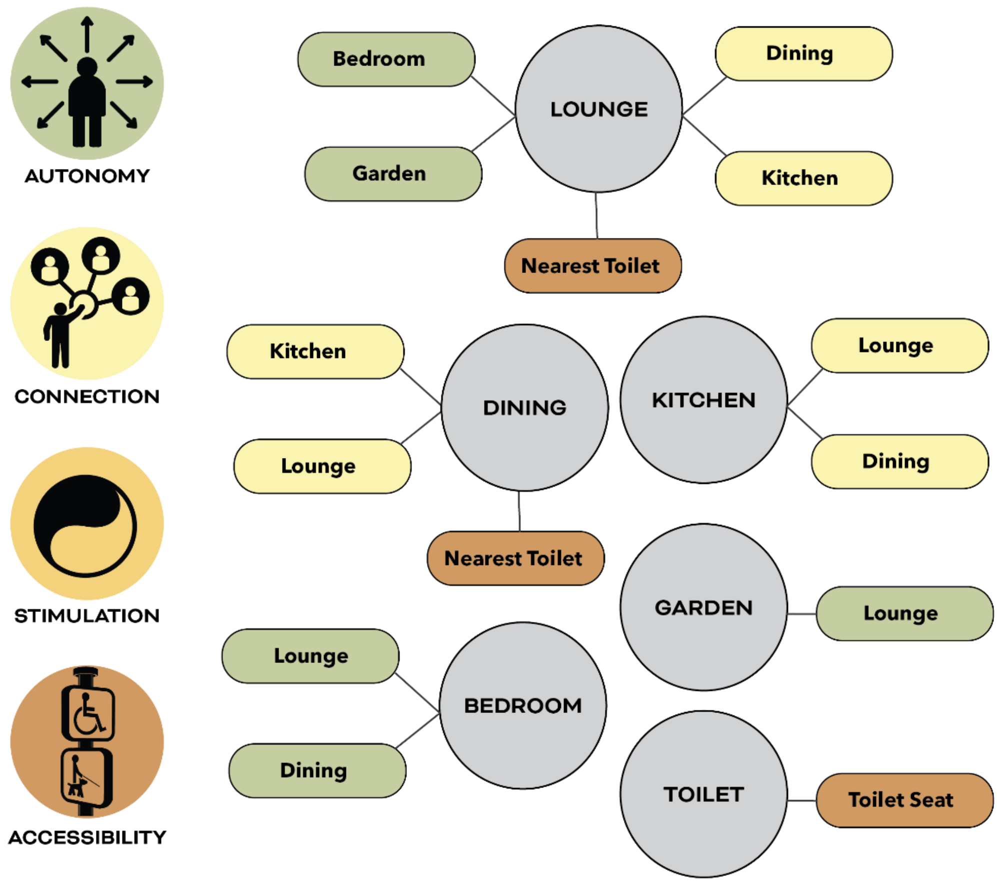


Figure 17: wayfinding quality checks each of those spaces for visual sightlines to adjacent spaces

Possible points per room function

Room function	Autonomy	Connection	Stimulation	Accessibility
Lounge	4	4	-	1
Dining	0	4	-	1
Kitchen	0	4	-	0
Bedroom	4	0	-1 to 1	0
Garden	2	0	-	0
Toilet	0	0	-	1
Staff (or corridor)	0	2	-1 to 1	0
Possible Points	10	14	-2 to 2	3

Figure 18: Possible points given per soft design criteria category

3.4.2 Assessment Indicator Thresholds

Each assessment indicator is assigned its own threshold, with each threshold corresponding to a point value to adds up to the final assessment of wayfinding quality. These points are then aggregated to determine whether a space is likely to promote better wayfinding. The scoring process is conducted for each space individually, such as the living room for two of the design criteria, and the bedroom for three of the design criteria. The scores for each space are then combined to assess the overall quality of the floor plan, providing both an overall performance value and detailed performance values per distinct soft design criteria.

In terms of stimulation level, balance is sought, acknowledging the need for some level of stimulation while emphasizing the importance of balancing to an acceptable range. The thresholds are defined here as general guidelines but might be different from person to person which can also be influenced by age-related hearing abilities influencing sensitivity to higher frequency or difficulty of speech understanding in noisy environments (Devos et al., 2019). The stimulation score aims to approach zero, indicating that the stimulation level aligns with individual needs, such as maintaining visual stimuli at a human scale and minimizing background noise in private areas. However, individual preferences may vary, with some individuals preferring more stimulating environments over quieter ones. In this scoring system, under-stimulated floor plans receive a negative value, while over-stimulated plans receive a positive value.

3.4.3 Expert Validation of Thresholds and Weights

The wayfinding performance indicators allow us to provide a granular scale system to determine the effectiveness of certain DDP being met and to estimate to what degree it is fulfilling its condition. This process should be taken with careful consideration to specific care facility by identifying the clinical profile of users, acceptable thresholds for visual and auditory stimuli. During this thesis, we take the 'universal' approach to assessing for DDP similar to the Plan-EAT (Quirke et al. 2021) approach, explained in the literature review, where each criterion is determined as a point per each DDP category. Therefore, this is a recommended area for investigation for further research to determine how DDP performance indicators can be determined and weighted based on individual needs and abilities.

On an individual criterion, queries from the EAT checklist indicate all visual access items addressed are indicated with two possible answers: yes (getting a point) and no (not getting a point). In this thesis project, we introduce three possible ways to assess the quality of visual sightlines by having three distinct categories: 0 for insufficient, 1 for sufficient, 2 for preferred. The preferred distinction is intended to provide feedback on layouts that are ideal on an individual criterion level.

The ranking is intended to be granular to distinguish between better performing plans that have slight spatial design variations, thereby exploring variable design options during the design selection stage of architectural design with the possibility to get performance assessment feedback on strengths and weaknesses for a floor layout with respect to wayfinding quality.

Dementia Design Principle Performance Indicators

Appendix A: Soft Criteria Performance Indicators

	Criteria Name	Cr.ID	Method	Weight	Not Sufficient	Sufficient	Preferred	Notes
PERSONAL AGENCY	**Lounge to Bedroom Door Visibility** Clear line of sight between bedrooms and lounge areas	1.1	Isovist grid	1	0 - 0.35	0.35 - 0.75	>0.75	not sufficient = 0 points sufficient = 1 point preferred = 2 points
	Bedroom to Lounge Visibility The lounge room is identifiable when leaving the bedroom	1.2	Isovist grid	1	0 - 0.35	0.35 - 0.75	>0.75	
	Bedroom to Dining Visibility The dining is identifiable when leaving the bedroom	1.3	Isovist grid	1	0 - 0.35	0.35 - 0.75	>0.75	
	Lounge to Garden Exit Visibility Clear lines of sight to outside areas / door from lounge	1.4	Isovist grid	1	0 - 0.35	0.35 - 0.75	>0.75	
	Criteria Name	**Cr.ID**	**Method**	**Weight**	**Not Sufficient**	**Sufficient**	**Preferred**	**Notes**
SENSE OF CONNECTION	**Lounge between Dining Visibility (both ways)** Clear lines of sight to from dining to lounge room	2.1	Isovist grid	1	0 - 0.35	0.35 - 0.75	>0.75	not sufficient = 0 points sufficient = 1 point preferred = 2 points
	Lounge between Kitchen Visibility (both ways) Clear lines of sight to from lounge room to kitchen	2.2	Isovist grid	1	0 - 0.35	0.35 - 0.75	>0.75	
	Dining between Kitchen Visibility (both ways) Clear lines of path to from dining room to kitchen	2.3	Isovist grid	1	0 - 0.35	0.35 - 0.75	>0.75	
	Corridor to Lounge Visibility Visual connection between corridor to lounge	2.4	Isovist grid	1	0 - 0.35	0.35 - 0.75	>0.75	
	Criteria Name	**Cr.ID**	**Method**	**Weight**	**Under-Stimulated**	**Balanced**	**Over-Stimulated**	**Notes**
BALANCED STIMULATION	**Sound Separation between vibrant and quiet areas** Can the noise from kitchen reach the private areas?	3.1	Distance of public to private	1	<0	0	>0	Estimates the degree of sound separation from living to bedroom. It takes into acount the centroid distances of both areas and number of intersecting walls.
	Acoustic Wayfinding Cues Can resident kitchen acitivies be heard from bedrooms?	3.2	Received Sound	1	<20 dBA	20 - 30 dBA	>30 dBA	Estimates the presence of sound eminating from kitchen spaces received from the corridor
	Criteria Name	**Cr.ID**	**Method**	**Weight**		**No**	**Yes**	**Notes**
ACCESSIBILITY	**Dining to Toilet Visibility** Clear lines of path to from dining room to private toilet	4.1	Centered Isovist	1		0	1	
	Lounge to Toilet Visibility Clear lines of path to from living room room to private toilet	4.2	Centered Isovist	1		0	1	
	Toilet Door to Toilet Seat Visual connection between staff location to lounge	4.3	Centered Isovist	1		0	1	

Score Tally	Points possible	Not Sufficient	Fulfills All Criteria	Ideal
Personal Agency	10	0 - 3	4	0 - 8
Sense of Connection	14	0 - 3	4	0 - 8
Accessibility	3	0 - 2	3	

Balanced Stimulation	Points possible	Under-Stimulated	Balanced	Over-Stimulated
	-2 to 2	<-1	0	>1

Figure 19: Preliminary scoring system for evaluating design criteria based on their assessment indicators

under stimulated = -1; balanced = 0; over-stimulated = 1

Soft Criteria	Performance Indicator	Under-Stimulated	Balanced	Over-Stimulated	Weight
Balanced Stimulation	3_1	0-20 dBA	20-30 dBA	> 30 dBA	1
	3_2	<20 dBA	20-30 dBA	>30 dBA	1
Total Score		<0	0	>0	

Table 1: Measuring the stimulation level in the floor layout emanating from the common kitchen area and received along the corridor

not sufficient = 0 sufficient = 1 preferred = 2

Soft Criteria	Performance Indicator	Not Sufficient	Sufficient	Preferred	Weight
Autonomy	1_1	≥0-0.35	>0. 35-0.75	>0.75	1
	1_2	≥0-0.35	>0. 35-0.75	>0.75	1
	1_3	≥0-0.35	>0. 35-0.75	>0.75	1
	1_4	≥0-0.35	>0. 35-0.75	>0.75	1
Total Score		<4	4	>4	

Soft Criteria	Performance Indicator	Not Sufficient	Sufficient	Preferred	Weight
Connection	1_1	≥0-0.35	>0. 35-0.75	>0.75	1
	1_2	≥0-0.35	>0. 35-0.75	>0.75	1
	1_3	≥0-0.35	>0. 35-0.75	>0.75	1
	1_4	≥0-0.35	>0. 35-0.75	>0.75	1
Total Score		<4	4	>4	

Soft Criteria	Performance Indicator	Not Sufficient	Sufficient	Weight
Accessibility	4_1	≥0-0.10	>0.10	1
	4_2	≥0-0.10	>0.10	1
	4_3	≥0-0.10	>0.10	1
Total Score		0-2	3	

Table 2: Determining the visual access quality based on the percentage of the visual access.

3.5 Limitation of Scope

In the scope of the thesis, only performance indicators related to supporting wayfinding and describing navigational quality are examined, in particular indicators that are taken directly from Environmental Assessment Tool (EAT) checklist that is based on the Flemming & Bennett Dementia Design Principles published in their handbook (2017), which the literature suggest as to being one of the most comprehensive checklists for evaluating existing care facilities given how many times it has been observed to be cited in other researchers working in this field. Moreover, the indicator selection were chosen on the basis that they can be assessed using ray-based methods to perform the assessment (such as isovist analysis, explained in the next chapter). The decision has been made to maintain the consistency of the assessment process, keeping the data type/format consistent, and specifically explore effectiveness of perception-based assessment method such as the isovist in describing the wayfinding quality of indoor environments from the point of view of a person with dementia. It is recommended therefore to examine other physical indicators influencing wayfinding quality that is outside the EAT checklist/handbook that are also important in supporting wayfinding, such as articulation of corridors, spatial hierarchy, position of common areas in relation to corridors, number of doors, corridor path length, and so on. Due to the limitation of the timeline for the thesis project, it was not possible to computationally measure all performance indicators to provide an assessment on a categorical level, i.e. for autonomy, therefore, more work needs to be done to computationally assess the entire list of performance indicators, as well as adding non-visual-access-based indicators to support autonomy.

The architect works in various levels of abstraction to represent the built environment throughout all of project phases. But in the design phases, the most useful way to communicate spatial quality is through floor plans which include information such as walls, doors, windows, and zones. Floor plan information in the early stages usually consist of bubble diagrams of spatial organization, and later on more defined by drawing the spatial organization in 2D plan views where each room/function is represented with a perimeter outline. In this step, the floor plan plays a critical role in communicating spatial qualities and provides assumptions on where walls will be positioned, doors to support optimal circulation, window for optimal views and daylight, and sometimes rough zones for furniture and fixed appliances. Traditionally the process is done with sketching different floor layouts and comparing them with the design brief drafted by the architect to verify if all the area and adjacency requirements have been met. It is in that step that some decisions are being made that includes wall positions and doors. The scope of this thesis is to propose a floor plan assessment tool with respect to soft design criteria that improve wayfinding quality for building users living with dementia. It is precisely in this phase that validation on design options is valuable in streamlining the design process and improve the likelihood of arriving at an optimal solution within in a timely fashion that will indeed improve the quality of living of a very vulnerable user group. User preference related to desired level of stimulation can also be defined in the client's design brief and the architect's program of requirements which is also outside the scope of this thesis since that is project-specific, and the spirit of this thesis is to develop a universal approach to evaluating wayfinding quality then coupling it with an AI model that can be later fine-tuned per project specifications or user preferences/conditions.

Anything else that gets decided at a later project phase or does not have a simple way to represent that in floor plan are excluded from the scope of this thesis. This is a very difficult decision, but this exclusion have been made to narrow the scope of this thesis into specifically exploring supportive tools for the early stages of design related to indoor wayfinding quality influenced by wall positioning. A single AI model will never be able to fully capture all the nuances of the design process which necessitates further investigation on how AI can support the design development of dementia care spaces in different stages of a project's life. An inherent limitation with designing in 2D is the missing third dimension. Visual access should include all three dimensions which at this stage is acknowledged to be a limitation of both the early stage process and the proposed AI framework that does not yet include sectional or 3D information in the assessment, simply because 2D format (both floor plans and sections) are more common than the 3D representations of physical or digital models. The sound modelling also suffer greatly when treating space as a 2D plane by excluding the ceiling height.

Providing care for people living with dementia presents a profound task towards the pursuit of architecture of wellbeing. The four (soft) design criteria only address qualitative aspects found in the built environment based only on one handbook out of several available (Margaret P. Calkins et al. 2022) which is inevitable to have excluded DDP criteria and design recommendations which did not make it in this study, which warrants a systematic review of all available evaluation methods for care facilities to get a better understanding of their scope, strengths, and limitations. Moreover, there are many more indicators which are not related to spatial design that influence perceived wellbeing that could not be taken into account which includes operational aspects of a care facility, the quality of the care provided, the training level of staff, the site location and the neighborhood, the visiting policies of the care facilities, the provisions for medication, the provisions for privacy, the security measures, quality of personal relationships, community events programming, group activities, access to therapy, and so on. It is therefore critical to holistically examine the overall project's quality, not only spatial design criteria, and the responsibility lies on the architect to advocate for universal design principles as a high priority and involve experts in the design stage to ensure the project's success.

4 Measuring Indoor Wayfinding Quality

4.1 Indoor Wayfinding Performance Assessment Method

Floor plans should be able to be measured precisely to describe its indoor wayfinding quality with respect to DDPs, a critical step towards evidence-based design. The usefulness of the wayfinding quality assessment is that it tests floor layouts using isovist measures to determine the exact wayfinding quality described in numeric values whether it is ideal/preferred (2), sufficient (1.5) or insufficient (0). The fundamental rationale for the assessment is to test whether the DDPs from the EAT have been met by answering the query items from the Plan-EAT checklist. Furthermore, the assessment results should give us insights on the extent of compliance with the defined four soft design criteria mentioned in the earlier chapter. The objective of the assessment is to devise a method to describe the qualitative design criteria related to wayfinding while also satisfying the conditions described in the EAT checklist. More critically, provide the assessment results in a numeric format that a computer can understand and interpret. The assessment method should also provide a more granular rating system that can distinguish between subtle variation in the floor plan and how it impacts the overall design criteria.

The potential outcome of this methodology is an algorithm that can assess wayfinding quality of a layout based on floor plan geometry and store the data to interpret the results and classify floor plans based on their wayfinding quality indicators.

4.1.1 Isovist Method

A common method used in quantifying visual connection is the isovist method, which was coined by Clifford Tandy in 1967, referring to the root word "iso-" from Greek, [isos meaning "equal" in English] and vista from Italian meaning "view" in English as a way to provide a permanent record for architectural and landscape spaces providing a viewshed, from "the inside out", from the point of a person's perception. Michael Benedikt later in 1979 introduced an analytical method of isovist measurements to record the properties of such as polygon perimeter and area from a single vantage point providing local properties of space (Turner et al., 2001).

Using the information provided by the isovist, we can determine whether an area is seen from a point in space. We can also determine how many times an object is seen from all possible points in space. Additionally, we can understand spatial perception features that influence perceived openness by examining the polygon area and its perimeter.

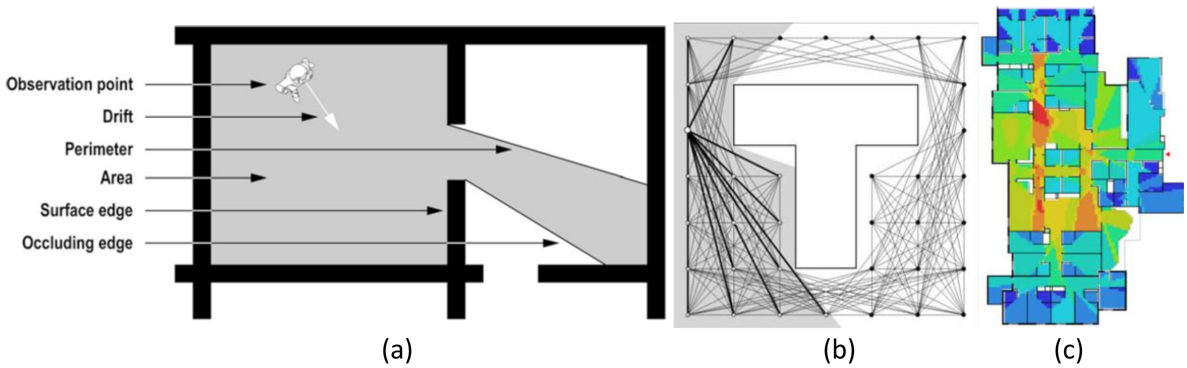


Figure 20: [a] an isovist polygon highlighting visible areas on the plan (Ostwald & Dawes, 2018); [b] an example of first-order visibility graph showing a pattern of connection for a simple configuration (Turner et al. 2001); [c] visibility graph analysis showing visual connectivity on a floor plan sample for dementia care facilities (Hing-wah et al. 2018)

Moreover, analysis of polygon area and perimeter facilitates understanding of spatial perception features influencing perceived openness. In the context of scale perception, isovist analysis can provide valuable insights into how space is experienced.

4.1.2 Assessing Wayfinding Quality

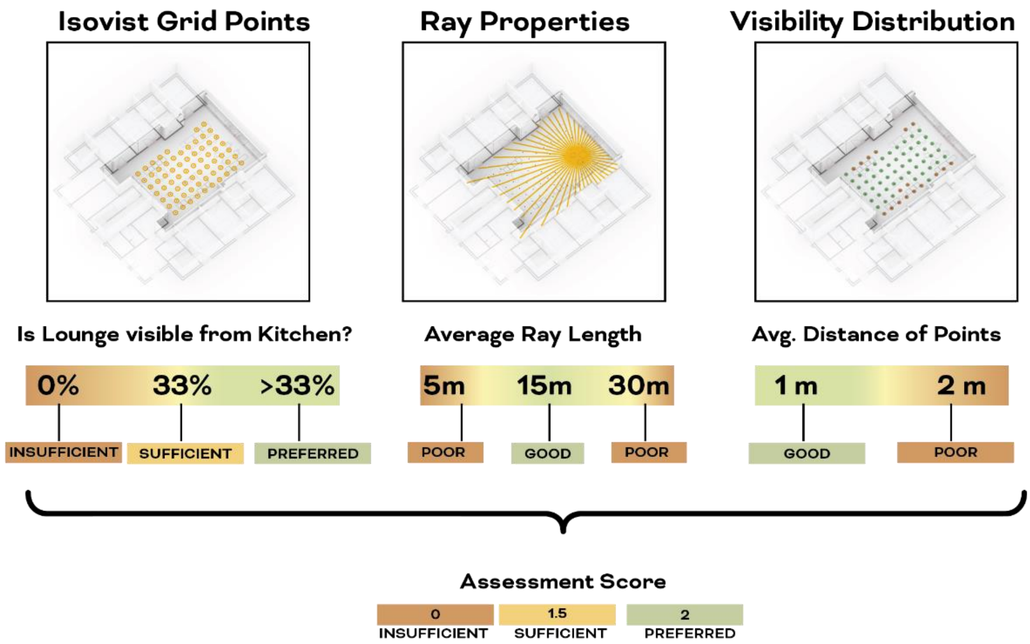


Figure 21: Assessment of wayfinding quality is determined by the isovist measures and added up to a final assessment score for wayfinding quality label.

Wayfinding quality is assessed using grid-based test points where each test point perform an isovist operation and store the numerical value to process the results. To evaluate the quality of wayfinding of a given floor layout, three different processes are proposed:

1. Isovist Grid Point: calculates the total percentage that satisfied the criterion.
   The rationale behind is based on the DDP requirement for clear sightlines between two spaces.
2. Ray Properties: calculates the average sightline length
   The rationale behind it is to estimate the usability of visual access. If a space is too far away it might feel distant or indistinguishable enough to be useful, whereas short sightlines could indicate poor visibility in general and overly-compact space.
3. Visibility Distribution: calculates the continuity of visual access in space by estimating the number of zones in the test area that suffer from poor visual access.
   The rationale behind it is to award points to zones that have consistent visual access across the test area and dock a point for excessively fragmented areas that do not have equal visual access quality.

These 3 operations describe the current definition of wayfinding quality for dementia-specific residential layouts that can be added up to give the final assessment outcome on the evaluated quality. Visual access measuring sightline being the most important factor, and gets penalized for inappropriate poor visibility due to distance or fragmented visual access in the test zone.

The outcome for visual access can be labelled as insufficient which does not meet the minimum threshold requirement for visually-connected spaces, sufficient which meets a bare minimum for visually-connected spaces but may suffer from scale problems or fragmented quality across an area, and finally, preferred which meets the recommended visual access requirements with good sense of scale and consistent across the entire test area.

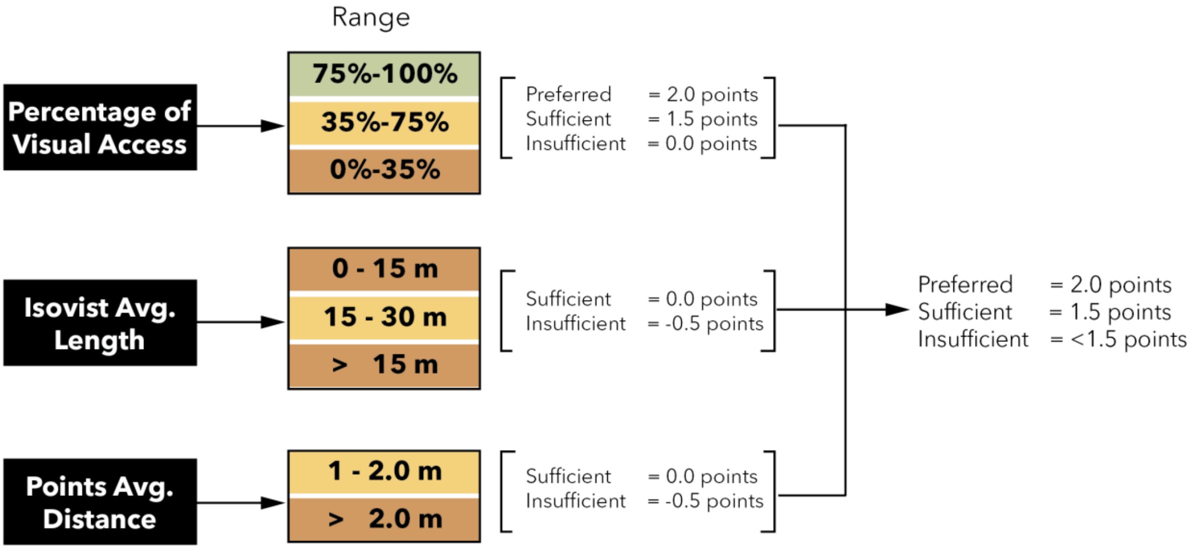


Figure 22: visual access is the main criterion for assessment. Isovist properties and average point distances are additional constraints to differentiate between spaces that have inconsistent visual access.

Wayfinding quality is characterized from the perspective of one room function. The literature emphasized the importance of sightlines surrounding the common areas. For example, the living room can be tested for visual access, which are known to support independent wayfinding, by calculating the sightlines to the nearest toilet, kitchen, living, corridor, main entrance, garden, and occupant bedrooms/housing unit. The same sightline test can be taken across all room functions, i.e. from the point of view of users occupying the kitchen, dining, corridors, and so on.

4.1.3 Sound Modelling

The sound environment is shaped by the properties of geometry and material. Sound, in addition to other stimuli such as smell and color, can support wayfinding for people living with dementia. In this thesis, we reduce the complexity of sound modelling to a 2D plane to get a baseline measurement on how sound propagates in spaces based on general assumptions on expected sound intensities in the common areas.

This method of sound propagation is based on the image-source method (Allen & Berkley, 1979), which is a widely used method for model propagation and reflection of acoustic waves. The method done here uses points as particles of energy bounced on a specular surface where each time a ray is bounced, the scattered energy is subtracted with every bounce.

$$Lp(R2) = Lp(R1) - 20 \cdot \mathrm{Log10}(R2/R1)$$

Where:
Lp(R1) = Known sound pressure level at the first location (typically measured data or equipment vendor data)
Lp(R2) = Unknown sound pressure level at the second location
R1 = Distance from the noise source to location of known sound pressure level
R2 = Distance from noise source to the second location

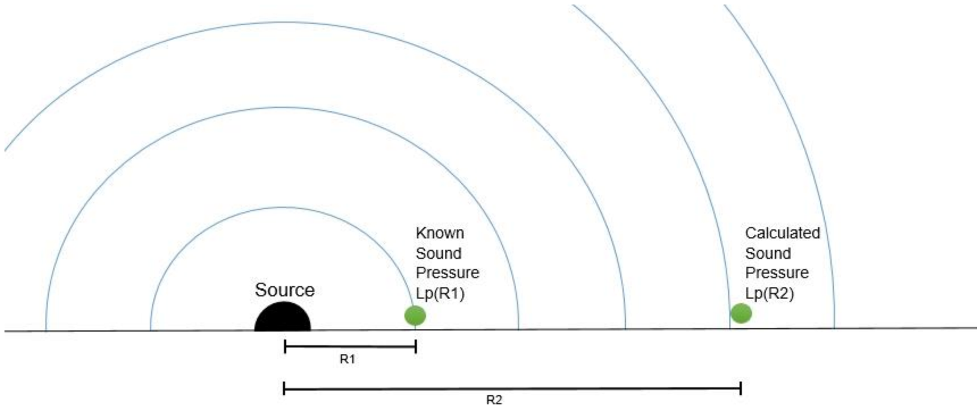


Figure 23: sound intensity decay over distance. (The Engineering Toolbox, 2005) illustration from wkc group.

The sound intensity and frequency band varies from room to room. Based on conversations with architects in the field during this thesis, it was highlighted that sound and smells coming from the kitchen is received pleasantly by its occupants for the most part, citing that the smell freshly baked cookies or the sound of a tea kettle can bring up positive associations in the occupant's mind, and entice them to approach the space where the sound/smell is coming from. If we examine a common household kitchen, we can see the sound intensities varies from activity to another. According to a sound experiment published in the Canadian Audiologist (Teder, 2014), dinner preparation sounds can peak at around 100 dBA measured 2 feet away from the sound source. The characteristic of the majority of household kitchen sound can be characterized by high-frequency and quickly dissipated in 130 milliseconds. Whereas in the living, the sound characteristics could be vastly different depending on the size of the household and the activities being performed (conversations, playing games, watching TV, playing music, etc.) and requires more detail for defining a reasonable assumption on the sound intensity level and frequency spectrum.

Material properties is assumed to be common gypsum-based drywall on timber studs which can have a sound absorption coefficient of 0.05 (The Engineering Toolbox, 2003).

Sound modelling in the form of sound propagation is intended to indicate where the sound leakage is occurring, calculate the sound decay over its travel path, and estimate the sound intensity at a receiving point, i.e. the corridor to determine whether or not it is reasonable to assume sound can support wayfinding abilities of occupants through acoustic stimulation. Although not developed in the thesis, this simplistic approach can also be useful for producing sound map intensities to show how generalized soundscape baseline will look like to identify concentration of noises or overlap of different noise sources that may interfere with one another in an undesirable way. The dominance of one noise source that clashes with another common space could therefore be estimated and visualized.

Two techniques are used to relate sound influence on space, the separation of sound between common and private areas, and sound intensity mapping to determine the characteristic of acoustic wayfinding cues. These techniques aim to assess factors such as sound transmission (perceived value range) and sound propagation to rate how sound is distributed in space. Environmental stimulation is associated with overall health and can be helpful for wayfinding; therefore, incorporating these sound measurement techniques alongside the visual connection assessment method can give us a more thorough assessment of wayfinding quality.

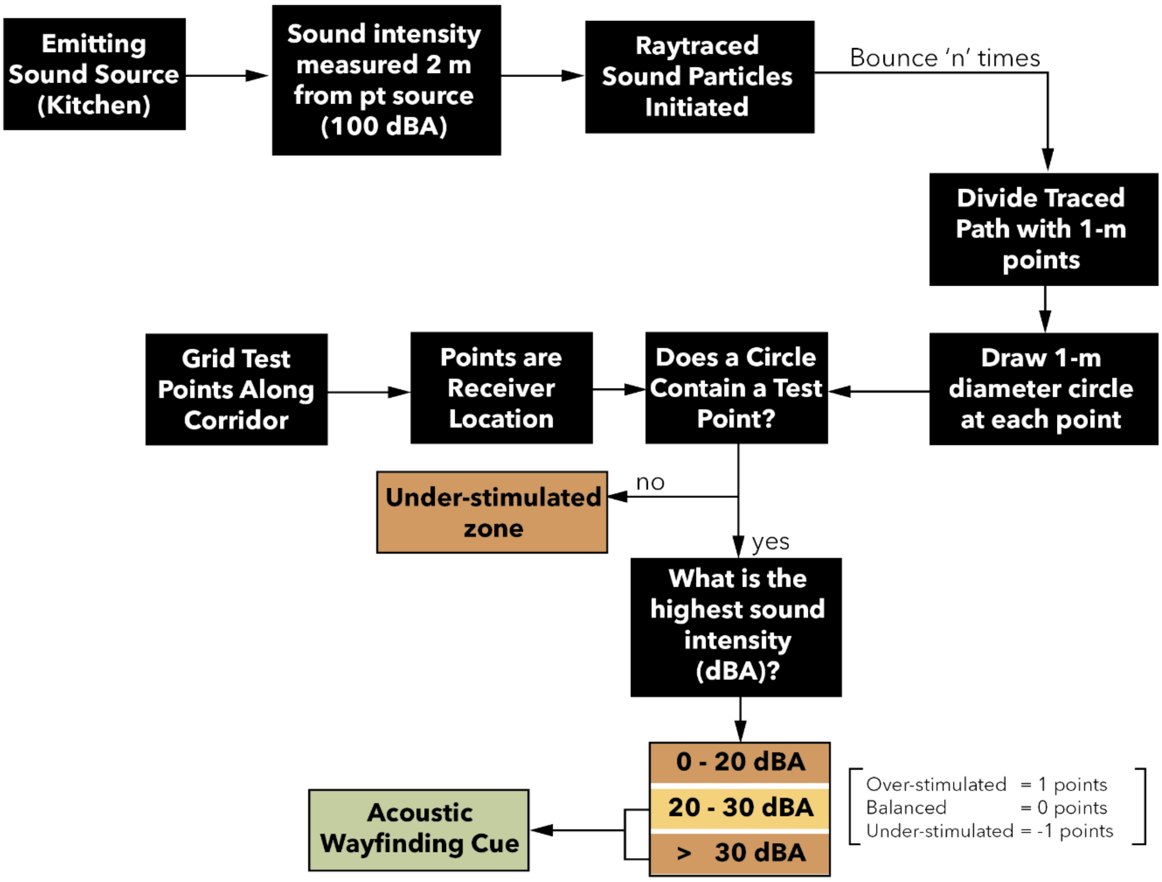


Figure 24: Testing for sound stimulation levels along a corridor based on expected levels of noise from common kitchen areas where the presence of a balanced stimulation is considered as a wayfinding cue

Sound stimuli can aid indoor wayfinding. Having noticeable and distinguishable sound while navigating a corridor is recommended as it can improve wayfinding ability of occupants based on Universal Dementia Design handbook, which states "it is helpful to use multi-sensory cues, such as sounds, to reinforce wayfinding and legibility." In this assessment, we simulate how sound particles travel in 2D space which helps us estimate the perceived level of sound intensity based on the number of bounces and distance from the source. This cue is useful when it is discernable to help associate sound with space, and audible enough to be detected considering hearing limitation and frequency range for elderly occupants (Devos et al., 2019). Another utility for using acoustic cues to prompt and encourage useful social interaction.

4.2 Performance Assessment Procedure

Analysis step is conducted inside of Grasshopper environment. Grasshopper is a visual-scripting platform serves as an extension to 3D-modelling software package Rhino3D. This software package is commonly used by architects and scientists in the built environment domain for its user-friendly interface, but importantly, to develop customizable scripts that can pair with 3D model information, such as building information.

4.2.1 Visual Access Analysis

Step 1: Extract an area's polygon for the test area (i.e. living room).

Figure 25: extraction of curve boundary

Step 2: Add test points to create isovist lines. 1-meter grid is selected to approximate the human-scale (Turner, 2001). Removing test points that are too close to the perimeter by specifying the minimum distance between curve boundary nearest point.

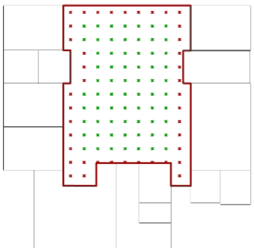


Figure 26: selecting the test grid for testing

Step 3: Trace out the isovist lines, test how many intersections occur between the sightlines and the target space.

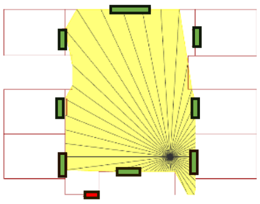


Figure 27: measuring sightlines and recording intersections with other areas in the layout

For Example:
Lounge Visual Access Assessment
Dining is **seen** from the selected point in the **lounge**
Garden door is **seen** from the selected point in the **lounge**
Toilet is **not seen** from the selected point in the **lounge**
....
Point n: [space] is [seen or not seen] from the selected point in the lounge

Step 4: Iterate through the entire grid and record the results for each test point. Store the information in a data recorder and later retrieve it by internalizing the data inside of a Data component.

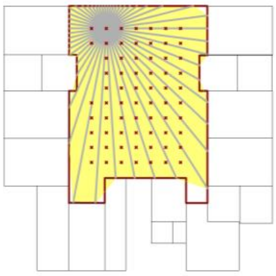


Figure 28: iterating through the grid with the same radial isovist lines and recording the intersections with other areas if any.

Step 5: Determine the final score in that given space by adding up the number of intersections between sightlines and target area and dividing them by the total number of test points which gives us the percentage of points that has seen the target space can be assigned a range here, for example:

≥ 0% - 35%	Insufficient
>35% – 75%	Sufficient
> 75%	Preferred

To further assess the wayfinding quality, store the average length of sightline by adding up the total length of rays and dividing them by the total number of rays used.

5 – 15 meters (poor visibility due to the space being too compact)
15 - 30 meters (appropriate)
>30 meters (indistinguishably far)

Distribution of visibility is also evaluated in this stage. The average distance between the test points that satisfy the criteria is tested. In the case where the average distance is low or consistent, it is therefore assumed most test points are adjacent to one another. Otherwise, if not then there are big gaps between some or most test points which indicate uneven visual connection quality. For example:

1 – 2 meter is the average distance between valid points; thus, it is **evenly distributed**.
2 meter is the average distance between valid points; thus, it is **unevenly distributed**.

4.2.1 Acoustic Wayfinding Cues

Step 1: create a point sound source in the common area (i.e. the Kitchen).

Step 2: Simulate the sound rays from the source tracing forward in space

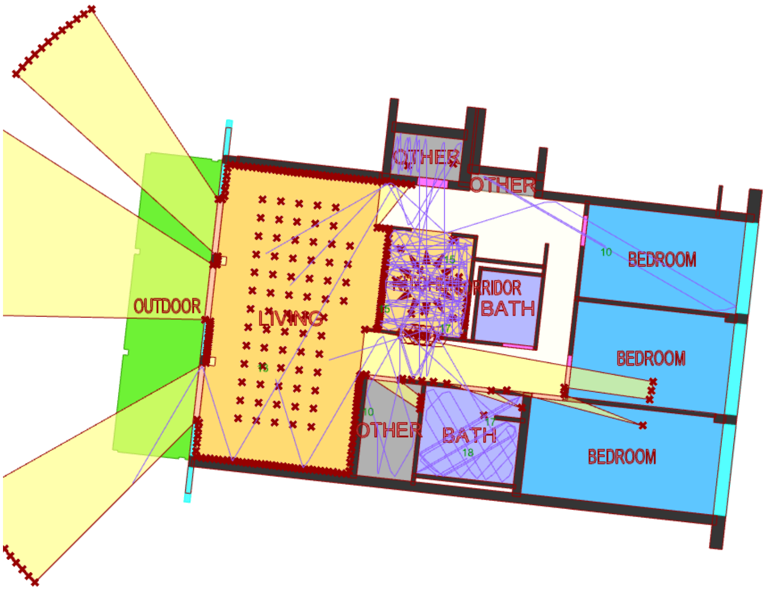


Figure 29: forward raytracing setup on Grasshopper providing the number of bounces.

Step 3: set the conditions for how far the sound travels and how many times it bounces depending on the material properties of the walls.

Step 4: how far is the reach of the sound in the corridor? How many bounces did it go through?

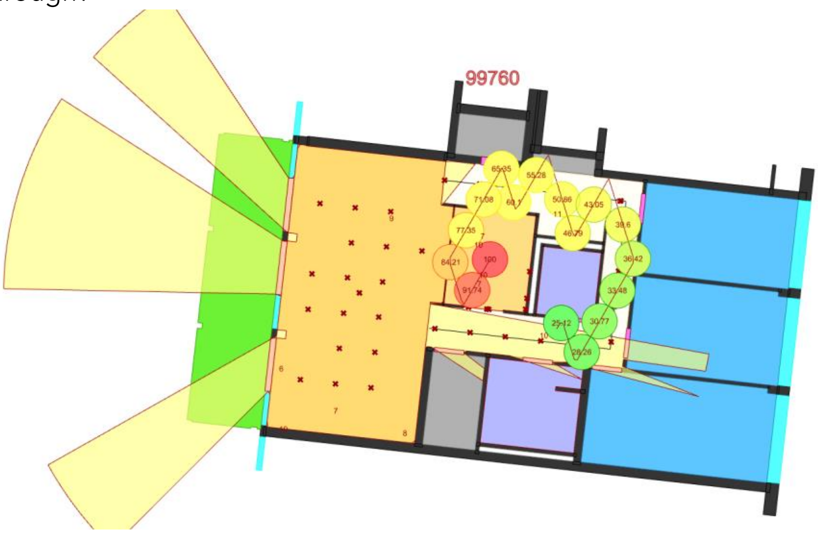


Figure 30: a preliminary stage for sound mapping of raytraced sound particle displaying intensities on various locations of the plan, here displaying only one sound particle.

Step 5: create a grid of points along all corridors and evaluate whether the sound particle is within its radius of influence of the test point at 1 meter in diameter. Was there a point inside the test circle? What is the recorded dBA? Is the sound potentially discernable and audible?

If there are not too many obvious dead zones, the corridor supports wayfinding through acoustic cues. Otherwise, if there are many dead zones and sound does not reach important areas, then it does not support wayfinding through acoustic cues. Alcoves along corridors might have an impact on sound propagation of acoustic wayfinding cues.

4.3.1 Sound Separation

Separation between private and common areas can be linked to the ability of occupants' wayfinding abilities. While the sound cues from common areas can be helpful for reinforcing wayfinding, excess background noise is linked to poorer health outcomes, and therefore should be balanced appropriately to ensure sufficient separation between common area and private area soundscapes.

In this analysis step, we try to describe the level of sound separation between common areas and private spaces (bedrooms/apartments). Separation between those two key spaces are one of the design guideline recommendations found on EAT checklist. Even though the sound stimuli in itself may have subjective perception, the perceived sound intensity (exceeding 50 dBA of background noise) has been shown to negatively disrupt sleep and overall health. The assessment aims to describe which bedrooms have good level of separations from common areas and which that don't so that users can choose the bedroom that fits their profile and preferences depending on the preferred level of stimuli and engagement in their surroundings.

The Sound Separation indicator tests the **resident Kitchen** area to the **Bedroom**.

Step 1: Extract the resident kitchen's centroid and this will be considered as the sound source.

Step 2: Extract the bedroom's centroid and this will be considered the receiver.

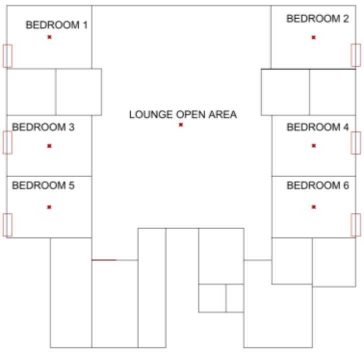


Figure 31:centroid of each bedroom is extracted and a common area such as kitchen or lounge.

Step 3: Count the number of intersecting walls and centroid distances.

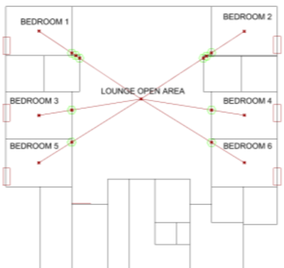


Figure 32: drawing a line between the two and counting the number of intersecting walls and centroid distances.

For example
Bedroom 1:
3 wall intersections between living and bedroom 1
3 meters centroid distance between living and bedroom 1
Perceived sound intensity from background noise: 40 dBA

The proposed equation for determining sound separation:

- Air absorption as a function of distance and frequency: the loss due to air absorption increase with the distance.
- The sound intensity reduction through walls by considering a typical absorption factor of 15%.
- Frequency range assumed here is high emanating from sharp objects colliding with each other in the kitchen area during meal preparation time.

Note: a maximum range for sound intensity measured from the bedroom centroid should be 40 dBA or less to avoid potential health risk associated with noisy environments.
Therefore:
> 20 dBA = under-stimulated
20-30 dBA = sufficient sound separation
< 30 dBA = over-stimulated

4.3 Application of Computational Assessment Workflow

The entire assessment algorithm is developed in Grasshopper environment and runs automatically by flipping through the entire dataset of floor plan geometry. The main purpose of the assessment algorithm is to have it be reliable enough to be able to work on all types of geometries received from the dataset. One of the common challenges being the orientation of plan and axis of grid point for visual access. The outcome is that the algorithm can reliably produce a grid test points for every possible living room geometry, draw the isovist rays, and count the number of intersections made between living to kitchen. The Grasshopper screenshots is available in Appendix 5.

4.3.1 Visual Access Script

The assessment algorithm was built in Grasshopper environment by retrieving the geometry of the dwellings directly from the Swiss Dwellings dataset to calculate the isovist properties.

Once the geometry has been isolated, the first algorithm takes the boundary of the living room and populates it with a grid point for initiating the isovist test. Then the results is logged in a data recorder which is subsequently exported as input data for the machine learning model training set.

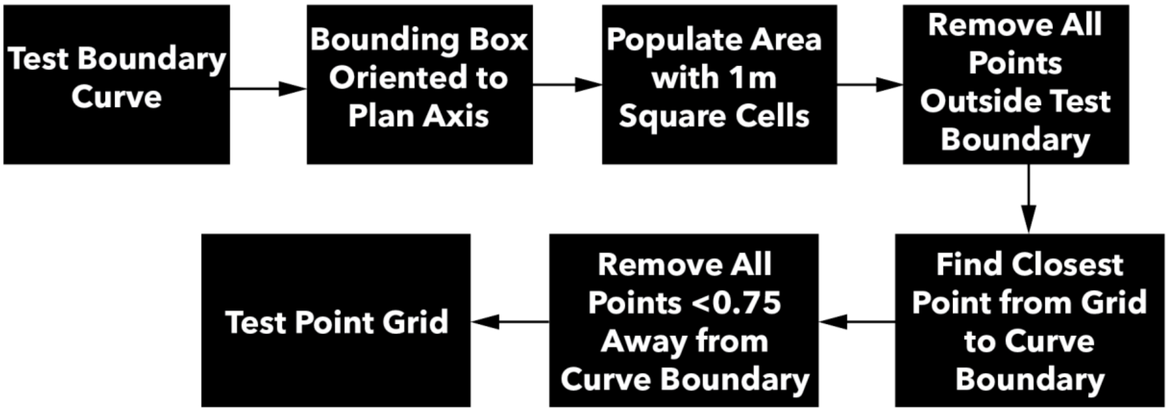


Figure 33: Flowchart for creating the test points inside of Grasshopper.

Inside of Grasshopper, there is a native component called *Isovist*. The isovist takes the geometry of the walls as obstacles and finds all intersection points. Once the intersection points have been identified, the lines are drawn from the test point to each intersection point that correspond to one another.

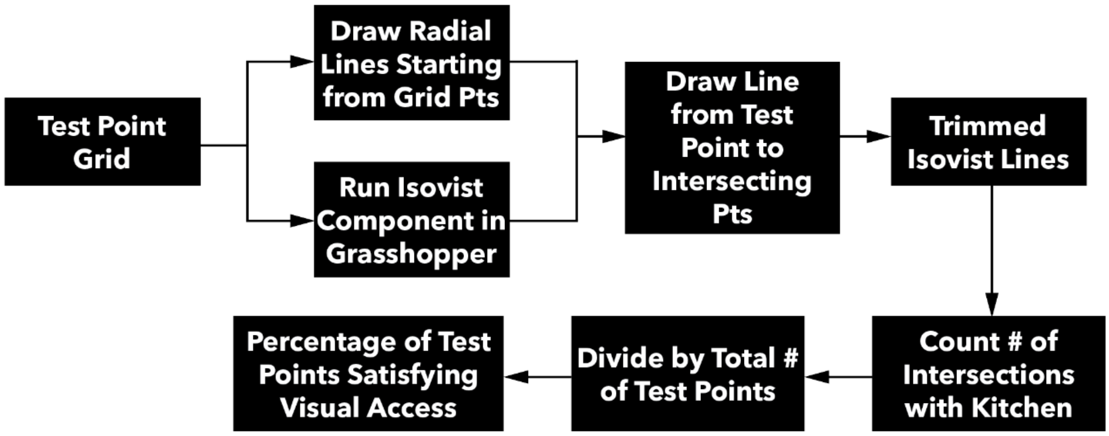


Figure 34: Flowchart for creating the isovists and finding the number of intersecting points for each test point to arrive at a percentage score for visual access.

The average ray length is calculated per floor plan and is also stored. The visibility distribution measures the average distance between all points that have satisfied the visual access requirements. The main important aspect for wayfinding is visual access but gets reduced if the visibility distribution is not even or if the isovist average length is too great / too little.

The variables that can be adjusted in the script are the following:

1. Test point spacing = 1 meter
2. Minimum distance from the perimeter wall = 0.75 meters
3. Isovist length = 30 meters
4. Radial isovist count = 24 rays
5. Obstacles/barriers = walls only (doors assumed to contain glazed panel with privacy shutters)

4.3.2 Sound Modelling Script

The sound modelling takes an existing component in Ladybug plugin library for raytracing. The code is modified to allow for sound decay over distance and absorption coefficient to record the sound intensity after a set number of bounces. The sound model shows where the sound travelled in the plan with corresponding estimated sound intensity level.

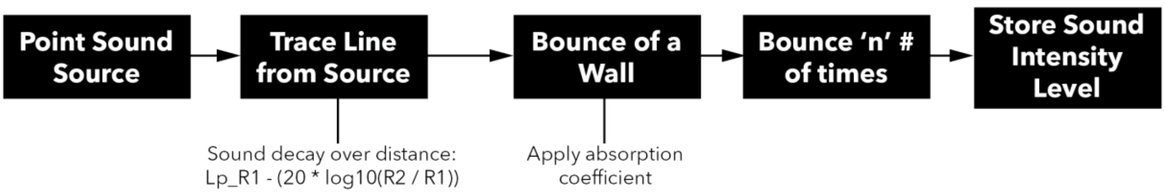


Figure 35: Sound modelling done via forward raytracing applying sound decay over distance and absorption coefficient per wall bounce.

4.4 Data Included in Building the Model

Several visual access indicators were stored in an Excel file, including sightlines from the living room to the kitchen, all toilets, all bedrooms, and dining area.

For this model, only two performance indicator are used—2_2 (living room to kitchen sightlines) and 4_2 (living room to toilet sightlines)— to predict wayfinding quality. Sound modeling was not incorporated into the model because of its complexity and the thesis timeline and remains a future area for research to provide a more comprehensive assessment of wayfinding quality based on multisensory data which can be used as training set for predicting wayfinding quality based on multisensory data.

4.5 Conclusion

The definition of wayfinding quality is described by three values: the percentage of test points satisfying the visual access condition, sightline length, and visibility distribution within the test space. The developed computational framework allowed for the systematic measurement of floor plan geometry imported directly from the Swiss Dwellings dataset where the test points in the living room are automatically populated to run the isovist analysis script to calculate the visual access quality. The information were recorded inside of Grasshopper and later exported to an .xlsx file to add as a new column feature in the Swiss Dwellings dataset.

The method serves as a starting point and will benefit from testing the different wayfinding quality indicators of floor layouts in experimental settings with real users to better calibrate the performance thresholds based on user behavior observed in the real world and in accordance with their clinical profile corresponding to the 3 dementia stages.

5 Machine Learning Framework

5.1 Machine Learning Methods

From the literature review, it was concluded that it is possible to use information generated from visual-perception analysis such as isovist and visibility graphs analysis to train an AI model with, and make use of the measures to correlate them with spatial features.

Initially, one assessment indicator for wayfinding quality is included to build a proof-of-concept to demonstrate that machine learning methods can be applied to assess dementia-friendly design criteria which took measurements of direct sightlines between living to kitchen. This data has expanded to additional sightline measures from living to bathrooms, and living to bedrooms.

Before proceeding with building the model, additional literature review was conducted to narrow down the specifics of the AI methods and algorithms. In specific, narrowing down the model architecture, machine learning methods, feature selection methods, and hyperparameter tuning methods.

5.1.1 Machine Learning Algorithms

Machine learning refers to the broader term for computer systems that are able to learn and improve their performance with data. These computer systems learn from examples and is able to make predictions based on the patterns it has seen from the data (Sedlmeier & Feld, 2018). The machine learning method will be used in this thesis to learn recurring patterns found in floor plan geometry in order to classify the wayfinding quality. The training will include isovist measures linked to wayfinding quality necessary to make a prediction and corelate them with building geometry features.

In general, there are several machine learning algorithms that are divided into different categories. Unsupervised machine learning method leverages unlabeled dataset to learn a function that best describe the data's inherent structure. A popular example of unsupervised learning is clustering similar data into groups without an explicit target value, instead it determines the function based on the patterns seen in the data (Sedlmeier & Feld, 2018).

Supervised learning algorithms learns a function based on a given pair of inputs corresponding to known output label (Sedlmeier & Feld, 2018). Supervised learning can be further divided into two main categories: regression problems where the output is a continuous numeric value, and classification problems where the output is a finite number of discrete labels (Sedlmeier & Feld, 2018). Supervised learning method is a subset of artificial intelligence which aims to fit complex data to extract hidden relationships between target variables (i.e. predicting a discrete class or continuous variable) and find the coefficient function based on the related problem. The trained model is then tested for its accuracy based on its correctness with classifying a set of predetermined attributes (Alloghani et al., 2020).

In this project, a labelled dataset of wayfinding quality classes and building features will be used, thereby making the supervised learning a suitable method for building the machine learning model with a classification task. A supervised learning method will be used to fit the data between wayfinding quality labels (target variables) and building geometry features (inputs). This method will allow us to correspond between the two variables: isovist measures extracted from the assessment results, and building geometry features. Wayfinding qualities are described as three discrete classes: 0, 1, and 2, thereby a multiclass classification problem will be used.

The most commonly used algorithms for multiclass classification problems are random forest, k-nearest neighbor, support vector machine, decision trees, and naïve bayes for supervised learning (Ross et al. 2023).

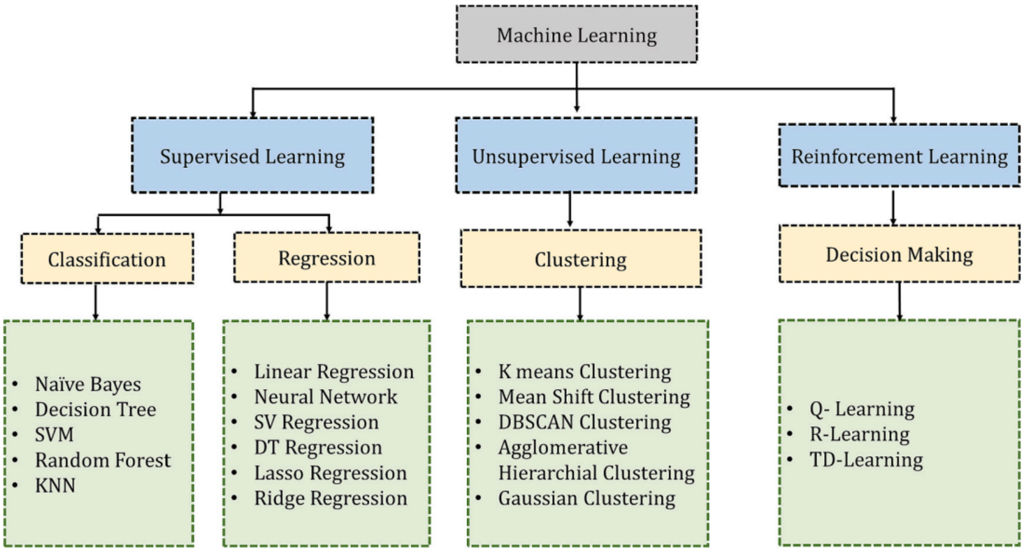


Figure 36: most common machine learning algorithms (Ross et al. 2023).

5.1.2 Random Forest Classifier

In the current number of target variables and dataset size of dwellings, Random Forest Classifier is a suitable option. Random forest classifier, based on the decision tree classifier, is a statistical machine learning algorithm for prediction (Breiman, 2001) which is a tree-based model involving "recursive partitioning of the given dataset into two groups based on certain criterion until it a predetermined stopping condition is met." (Schonlau & Zou, 2020). The advantage of this method is its interpretability where the decision tree can also be graphed and analyzed. It particularly works well with tabular data and especially shines with large feature sets. A limitation for this algorithm is that it can get computationally expensive for larger datasets.

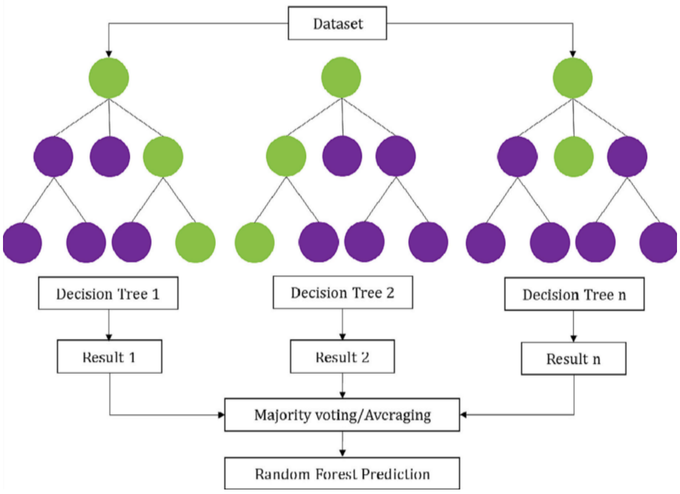


Figure 37: architecture of random forest (Ross et al. 2023).

With random forest classifier, feature importance is a method which is used by researchers to identify the most important features that affect the target variables. According to the authors, random forest was implemented in two stages. First, the entire dataset was classified, then feature importance was used to determine the most important feature influencing patient satisfaction with respect to indoor environments quality measures (Ali et al., 2022). Artificial neural networks were used in combination with random forest classifier to confirm the most influential feature for patient satisfaction. The study is particularly useful for this thesis project as it shows a successful implementation of two machine learning models to determine the perceived quality for a binary classification problem to predict a patient's satisfaction response based on indoor environmental quality controls described as numeric features such as temperature, sound level, and illumination levels.

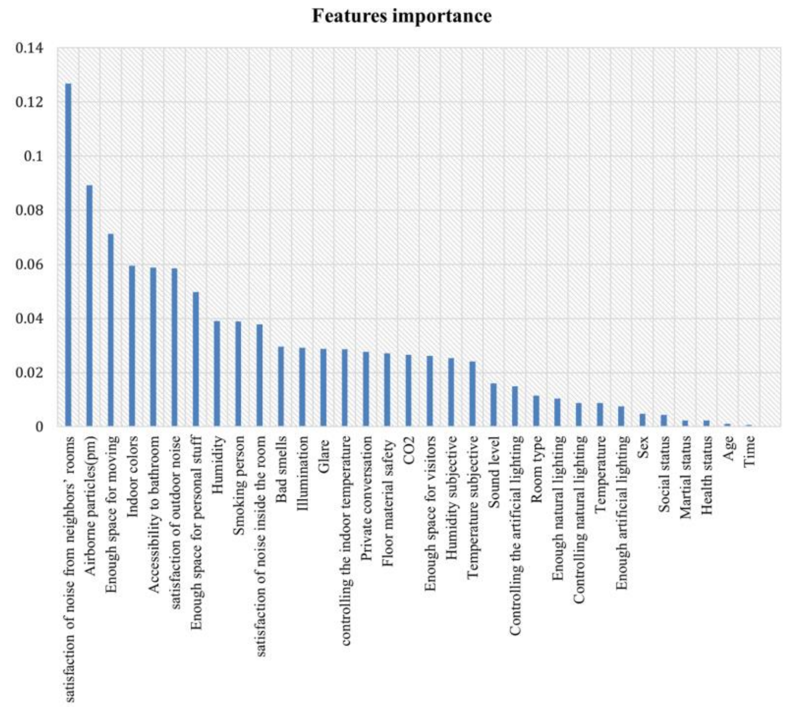


Figure 38: Feature importance plotted by the study indicating satisfaction of noise from neighbor's room is among the most important feature for determining patient satisfaction based on a sample size of 497 (Ali et al., 2022).

5.1.3 Artificial Neural Networks (ANN)

One of the most commonly used models is the multilayer perceptron (MLP), a type of artificial neural network (ANN), that can be used for multiclass classification problems of discrete values as well as regression for continuous values. This model architecture is useful for complex datasets where the relationships between features and the target variable are non-linear and difficult to model with simpler methods (Cybenko, 1989). In particular, deep neural networks perform well with the recognition of recurring patterns for large datasets and the discovery of the underlying functions (Sedlmeier & Feld, 2018) as well as the added benefit of scalability as the data expands to add more assessment indicators and floor plan geometry. The neural network provides a range of hyperparameter that can be tuned to improve the model performance and to avoid memorizing the data (also known as overfitting) by adjusting the learning rate of the model for example. Based on the AI support tools literature conducted earlier in the Literature Review chapter, neural networks were employed for datasets consisting of isovist and visibility graph analysis measures as variables (Tarabishy et al. 2020 and Johanes & Huang, 2022). However, one major limitation of the ANN is its susceptibility for overfitting due to its complexity which needs to be addressed in the development stages of the wayfinding quality assessment model.

Neural networks are based on the perceptron, the basic component of an ANN, which takes multiple input variables and multiplies them by their weight, adds bias term, and sums up the results. An activation function is applied for each perceptron which introduces non-linearity into the neural network (Abhishek & Abdelaziz, 2023).

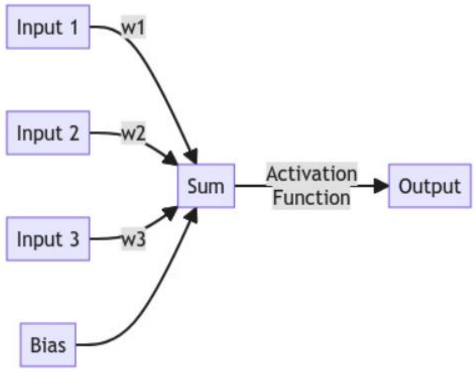


Figure 39: A single perceptron in a neural network process the inputs using activation function to help determine the output (Abhishek & Abdelaziz, 2023).

The most common activation functions being sigmoid, tanh, rectified linear unit (ReLu), and softmax. Activation functions are important for neural networks to capture non-linear features which is where a neural network shines (Pantalé, 2023).

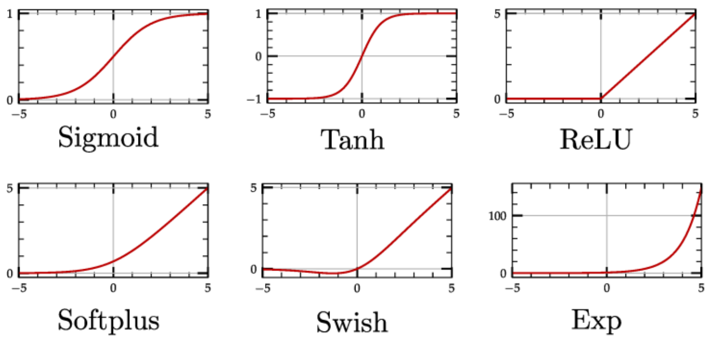


Figure 40: Example of activation functions used in ANNs (Pantalé, 2023).

5.1.4 Feature Selection Methods

Considering the novelty of machine learning models trained on wayfinding quality indicators for dementia care, special attention should be given to the feature selection strategy to better control the features this thesis introduces and evaluating them systematically in order to make useful observations on features that will help give insights for future project expansions. Similar studies that had novel machine learning-based models gave extra attention to the feature selection process and through a systematic process of elimination, feature combinations are discovered to build a more effective predictive model.

The wrapper-based feature selection (WFS) method is leveraged by researchers to home in on a feature set that is useful for their models. The method is based on the "greedy search method" because it considers every feature set selection possibility respect to the evaluation criteria (i.e. accuracy of predicting the target variable) using pre-determined classifier such as random forest or decision tree (Balogun et al., 2020). Although the WFS method is computationally expensive, it could lead to better results than trial and error because it tests all possible options. Other important feature selection methods include filter feature ranking (FFR) which is less computationally expensive and is based on the correlation coefficient. FFR evaluates the rank of features in a given dataset by considering the latent properties of a given dataset, which subsequently rank scores are generated (Balogun et al., 2020).

Filter methods are tested in architectural-structural research employing the wrapper method for feature selection of building features related to structural responses of tall buildings (Kazemi et al., 2024). The authors introduced the wrapper-based method of feature selection testing using the random forest classifier in addition to exhaustive methods performed in the study for the purpose of feature selection highlighting it being a novel approach to handling limited data sets in structural engineering research. The exhaustive method takes a sequential approach testing all possible combinations as it iteratively adds and removes features to examine the impact on the model's performance, yielding the best features for the learning process Kazemi et al., 2024). This method allows for the exploration of all possible feature combinations and provides the most comprehensive analysis. Given the small size of the dataset for this thesis project, the exhaustive method will be tested as the basis for feature selection for its comprehensive analysis benefit.

Table 2
List of features for the studied data set.

ID	Features	Data type	Range/values	Meaning
F1	Number of top plan sides	Discrete, integer	[3,13]	Integer number of the edges of the polygon used for the tall building top plan
F2	Number of bottom plan sides	Discrete, integer	[3,13]	Integer number of the edges of the polygon used for the tall building bottom plan
F3	Total gross area (TGA)	Continuous, float	$[6.95 \cdot 10^4, 7.06 \cdot 10^4]$ m^2	Sum of floor plan area for all stories of the tall building
F4	Height	Discrete, integer	[232, 236] m	Net height of the building, equal to the number of floors times 4 meters
F5	Aspect ratio (AR)	Continuous, float	[3.92, 5.24]	Ratio between the building height and the maximum width of bottom floor plan
F6	Diagrid degree at top	Continuous, float	[41.45, 61.18]°	Inclination angle, with respect to the horizontal plane, of diagrids at the top plan of the building
F7	Diagrid degree at bottom	Continuous, float	[61.01, 75.70]°	Inclination angle, with respect to the horizontal plane, of diagrids at the top plan of the building
F8	Diagrid degree, average	Continuous, float	[51.90, 67.25]°	Average of the inclination angles, with respect to the horizontal plane, of all diagrids in the model
F9	Total façade area	Continuous, float	$[2.84 \cdot 10^4, 3.63 \cdot 10^4]$ m^2	Side area of the building, including diagrid area and holes between diagrids
F10	Total amount of diagrids	Discrete, integer	[4522, 8568]	Number of vertical, horizontal and inclined diagrids
F11	Total length of diagrid members	Continuous, float	$[1.87 \cdot 10^4, 2.59 \cdot 10^4]$ m	Sum of the lengths of all diagrids
F12	Total mass	Continuous, float	$[7.74 \cdot 10^3, 1.05 \cdot 10^4]$ tons	Total mass in the model, accounting for all the finite elements included
F13	Height of the center of gravity	Continuous, float	[104.55, 110.31] m	Position of the center of gravity with respect to the bottom plan

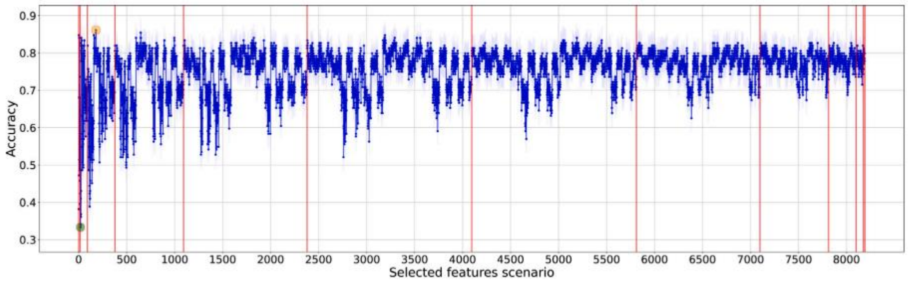


Figure 41: An overview of all architectural features tested in relation to structural responses where advanced feature selection and plotted accuracy curve for all possible 8191 possible feature combinations (Kazemi et al., 2024).

5.1.5 Test Split Method

Splitting the training set for building the model is a common technique to track the model's accuracy. Typically, there are three types of splits: the training set which is a dataset on which the model is trained on, a validation set which is a set used for tuning hyperparameters of the model, lastly an evaluation or test set which is used for the evaluation of the performance of the model (Abhishek & Abdelaziz, 2023). Another study showed that when using random forest classifier and artificial neural network for the purpose of assessing important features, it is critical to keep the split the same from the beginning of the process all the way to the end (Ali et al., 2022). In this thesis project, there are 256 dwellings with no null values. The data split will be in two sets: training at 70%, and validation at 30%. An additional test set saved aside from an earlier filtering process has 94 dwellings which will be reserved for evaluating the model's performance.

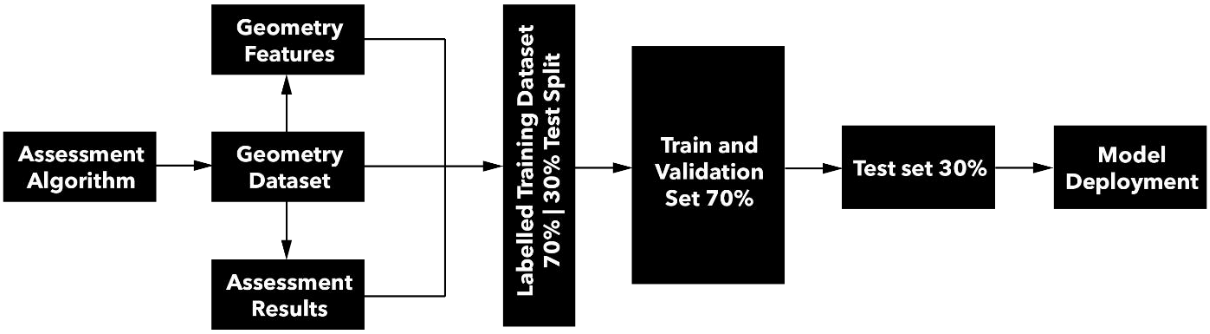


Figure 42: Machine learning training workflow describing the components of the dataset and the development methodology using train/validation split to assess the model's accuracy.

5.1.6 Evaluation Metrics of Machine Learning Performance

A common technique to evaluate the performance of a machine learning model is through confusion matrix which takes into account the number of true positives, true negatives, false positives, and false negatives, and is described in several metrics including accuracy of the model, precision, recall, and F1 score. Accuracy describes the overall accuracy of correct predictions, whereas precision focuses on the proportion of positive predictions that are actually correct. Precision is useful for assessing how well a model avoids false positives which demonstrates its ability to make accurate positive predictions. Recall, on the other hand, is the proportion of actual positive instances that are correctly identified by the model which is especially important when the cost of missing positive instances (false negatives) is high, such as in medical diagnoses. F1 is a useful metric when equal importance is given to both precision and recall which is a single metric as the harmonic mean of precision and recall (Abhishek & Abdelaziz, 2023).

$$Accuracy = \frac{t_{pos} + t_{neg}}{t_{pos} + t_{neg} + f_{pos} + f_{neg}} \qquad Recall = \frac{t_{pos}}{t_{pos} + f_{neg}}$$

$$precision = \frac{t_{pos}}{t_{pos} + f_{pos}} \qquad F1\ Score = 2 \times \frac{Precision \times Recall}{Precision + Recall}$$

Figure 43: the equations used in a confusion matrix to provide detailed metrics on a model's performance (Ross et al. 2023).

Multi-output models will have an additional metric for evaluation to understand how the model is overall model with respect to multiple outputs. For a strict evaluation of the multi-output model, we use the 'subset accuracy' which indicates the percentage of labels predicted that exactly match their corresponding set of true labels (Romeo et al., 2021; Jamthikar et al., 2022) where the higher the value the better. Hamming loss which serves to capture the fraction of incorrectly predicted labels by the model (SKLearn, Metrics and scoring)

$$\text{Accuracy score } (y_i, \widehat{y_i}) = \frac{1}{n_{\text{samples}}} \sum_{i=0}^{n_{\text{samples}}} 1(\widehat{y_i} = y_i)$$

Figure 44: Subset accuracy score that consider multiple classification outputs where y_i is true values and $\hat{y}$ is predicted value of the ith sample (Kim et al., 2022).

$$\text{hloss}(g) = \frac{1}{N} \sum_{i=1}^{N} \frac{1}{|\mathcal{A}|} |g(\mathbf{x}_i) \Delta \mathbf{y}_i|$$

Figure 45: Hamming loss takes the fraction of labels that are incorrectly labelled across multiple classification output where N is the number of test samples, y_i is the true label set for sample x_i, g is the multilabel classifier, and delta is the symmetric difference between the sets. (Yang et al., 2020).

For wayfinding quality, it is important for minimizing false positives where a labeled space having insufficient wayfinding quality as sufficient or preferred. The subset accuracy serves as a strict measure that accepts no false positives in the multi-output classification model. On an individual output level, recall will be a useful measure for minimizing false negatives where a space does have sufficient wayfinding quality but classified as insufficient.

5.1.7 Model Overfitting Mitigation Strategies

A fundamental issue in supervised machine learning is overfitting which prevents the model from generalizing well from observed data to unseen new data, an issue especially exacerbated by when the training set is too small in size (Ying, 2019). One way to prevent overfitting is to expand the training data. Other techniques can also be used to prevent overfitting. This includes early stopping by computing the accuracy at the end of each epoch and stopping the training if the accuracy on the validation set stops improving to determine when to stop (Ying, 2019). Regularization techniques can be used when the number of features increases and becomes complicated. An overfit model takes into account all features regardless if only some of them have very limited effect on the final output (Ying, 2019). A useful technique to use is L1 and L2 regularization to prevent overfitting which adds a penalty term to the loss function and encourage the model to have smaller weights, thereby reducing its complexity. Dropout is another regularization technique for neural network which randomly deactivates a fraction of the neuron in a layer to prevent them from contributing to the output which can yield to better generalized features as it cannot rely on a single neuron for determining the output. Batch normalization is another neural network technique to help with overfitting issues which normalizes the inputs to each layer by adjusting the mean and standard deviation, a useful technique for deep learning to accelerate the training process and reduce weight sensitivity to weight initialization (Abhishek & Abdelaziz, 2023).

A study on indoor environmental quality in a school building used an ANN to predict the predicted mean vote (PMV) and IEQ variables for a dataset of building simulation results based on a school in Seoul. They implemented a multi-objective genetic algorithm to search for optimal hyperparameter values including regularization amount (Cho & Moon, 2022). For complex tasks such as personalization of preference profiles of thermal environments with actual building occupants, regularization is an important strategy to control the complexity of the model and avoid overfitting (Lee et al., 2019)(Lee & Karava, 2020).

Overfitting prevention strategies will be tested in this thesis using a small selection of these techniques especially considering the limited data size for dwellings and the growing complexity of future expansion of more wayfinding quality indicators and additional features.

5.1.8 Neural Network Model Hyperparameters

A model's hyperparameters are variables that can be set within the machine learning algorithm to manage the training process, often selected manually prior to initiating the training. The study on patient's satisfaction provide a list of possible hyperparameters used for their neural network that performed well for predicting patient's satisfaction. According to their results, model 1 had the highest accuracy at 0.967% followed by model 4 at 0.953%. Furthermore, the accuracy had a slight increase by using three hidden layers using the same activation functions ReLu and Sigmoid with the same number of epochs (Ali et al., 2022).

	Parameters					Model compiler	
Model	# of hidden layers	Activation functions	Nodes	Epochs	Batch size	Optimizers	Loss function
1	1	Sigmoid	32	300	32	Adam	Binary cross entropy
2	1	Sigmoid	32	100			Mean squared error
3	2	Softmax	32	100			Binary cross entropy
		Sigmoid	1				
4	3	ReLu	32	100			Binary cross entropy
		ReLu	32				
		Sigmoid	1				

Figure 46: Hyperparameter settings tested in the neural network experiment for a dataset containing IEQ conditions and correlating it with patient's satisfaction captured from 497 hospital self-reported data surveys (Ali et al., 2022).

5.1.9 Hyperparameters Search Methods

Hyperparameter settings can be further improved by implementing the GridSearch algorithm from scikit-learn. The GridSearchCV function conducts an exhaustive search over specified parameter values while performing a k-fold cross validation (scikit-learn, GridSearchCV). CV stands for cross validation which is a k-fold cross-validation generator that randomly shuffles the data, divides the data into k parts, train the model on k-1, and evaluates it on the remaining data. This technique is used when the data size is limited where 5 or 10 folds is the most common (Abhishek & Abdelaziz, 2023). In this thesis project, the hyperparameter settings found by the GridSearchCV will be used as inputs for a new training model on a separate file with a new test split to avoid data leakage between the grid search and the final results of the validation set.

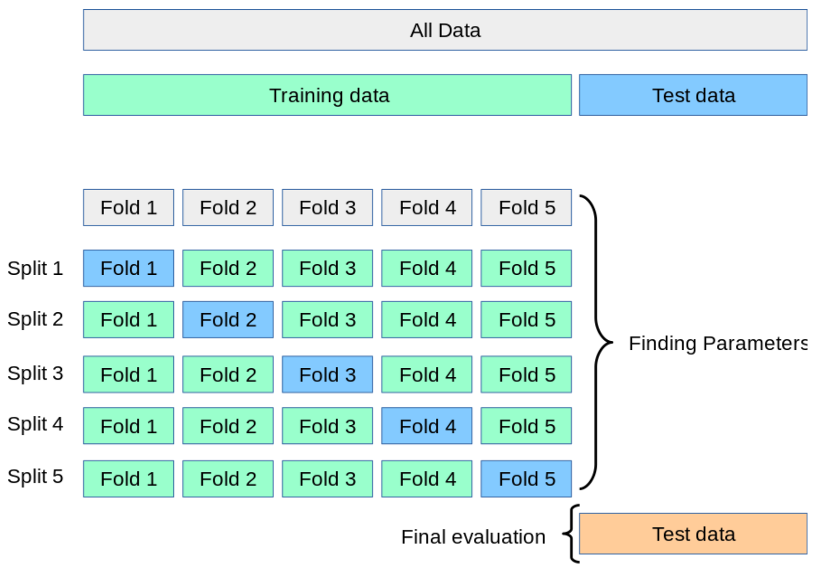
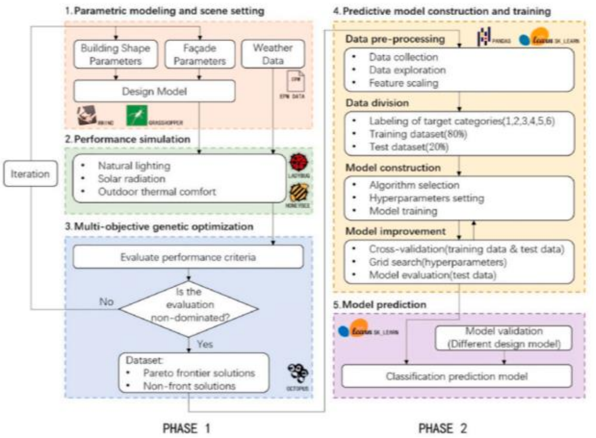


Figure 47: Cross-validation data shuffling (SKLearn, Cross Validation).

A study on developing a comprehensive performance assessment and rapid prediction of indoor and outdoor thermal performance of office buildings implements a combination of 10-fold cross validation and grid search to train and optimize the hyperparameters for 3 model algorithms on a data sample size of 6000 (Yan et al., 2022). The grid search is also useful for linear regression tasks employed by a study for predicting thermal sensation using ASHRAE comfort database to obtain optimal hyperparameters (Luo et al., 2020).



The tuned hyperparameters for Random Forest, LGBM, and AdaBoost.

Algorithm Models	Hyperparameters		
Random Forest	n_estimators 200	min_simples_leaf 30	min_simples_split 5
LGBM	n_estimators 150	max_depth 12	learning_rate 0.05
AdaBoost	n_estimators 150	algorithm SAMME.R	learning_rate 0.2

Figure 48: a grid search for 3 different algorithm models was conducted after the construction of the model and initial hyperparameter settings and training (Yan et al., 2022).

Randomized Search is another variant for exploring the hyperparameter space by randomly sampling a combination of pre-determined range of hyperparameter variables. Unlike the grid search which systematically evaluates all combinations in the grid, the Randomized Search randomly samples from the distribution of hyperparameter range a user assigns to it. Thie approach is far more computationally efficient, but it lacks the comprehensiveness of the Grid Search method. This is especially useful when the hyperparameter space is too large as it provides a good trade-off between exploration and exploitation (Peters, 2023). A relevant machine-learning study that developed a surrogate model that can relate building design parameters to performance outcomes, such as seismic loss and carbon emissions, implemented both randomized and grid search methods citing “a randomized search algorithm was applied” on the feature subset “to find the bounds on best-performing hyperparameters based on the training dataset, followed by a grid search algorithm to further tune hyperparameters. 3-fold cross-validation (CV) was used to avoid overfitting at each hypertuning method” (Zaker Esteghamati, 2021).

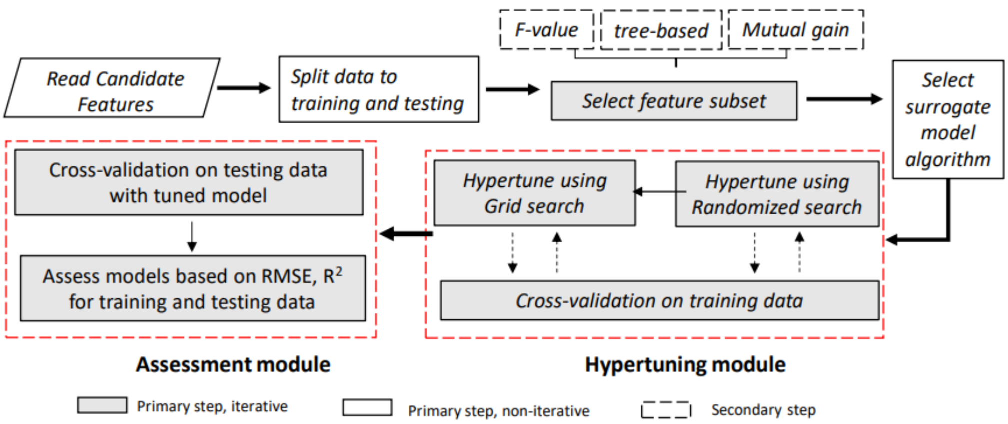


Figure 49: surrogate modelling framework applying both randomized and grid search to find the most optimal hyperparameters to a novel machine learning model to support resiliency and sustainability in the early design (Zaker Esteghamati, 2021).

5.1.10 Conclusion on Methods

In summary, given our dataset being labelled with wayfinding quality classes, the supervised method will be employed for building the model to correlate the class of wayfinding quality with building features. Considering the novelty of wayfinding quality for dementia care, feature importance will be implemented using random forest classifier to better understand the influence of features on the wayfinding quality. Moreover, a neural network will be the basis of the model architecture allowing for future expandability as the feature set (inputs) and wayfinding quality labels (output) grow in complexity. Moreover, feature selection will be done both trial-and-error approach as well as using the randomized search method to test for a small subset of features to get a wide overview of the impact of each feature on the predictive ability of the model as well as guide the hypertuning parameters. Finally, hyperparameter selection will be guided by the GridSearchCV with the parameter range based on the study (Ali et al., 2022) in order to find the optimal settings for building training the model and reporting the final accuracy of the model.

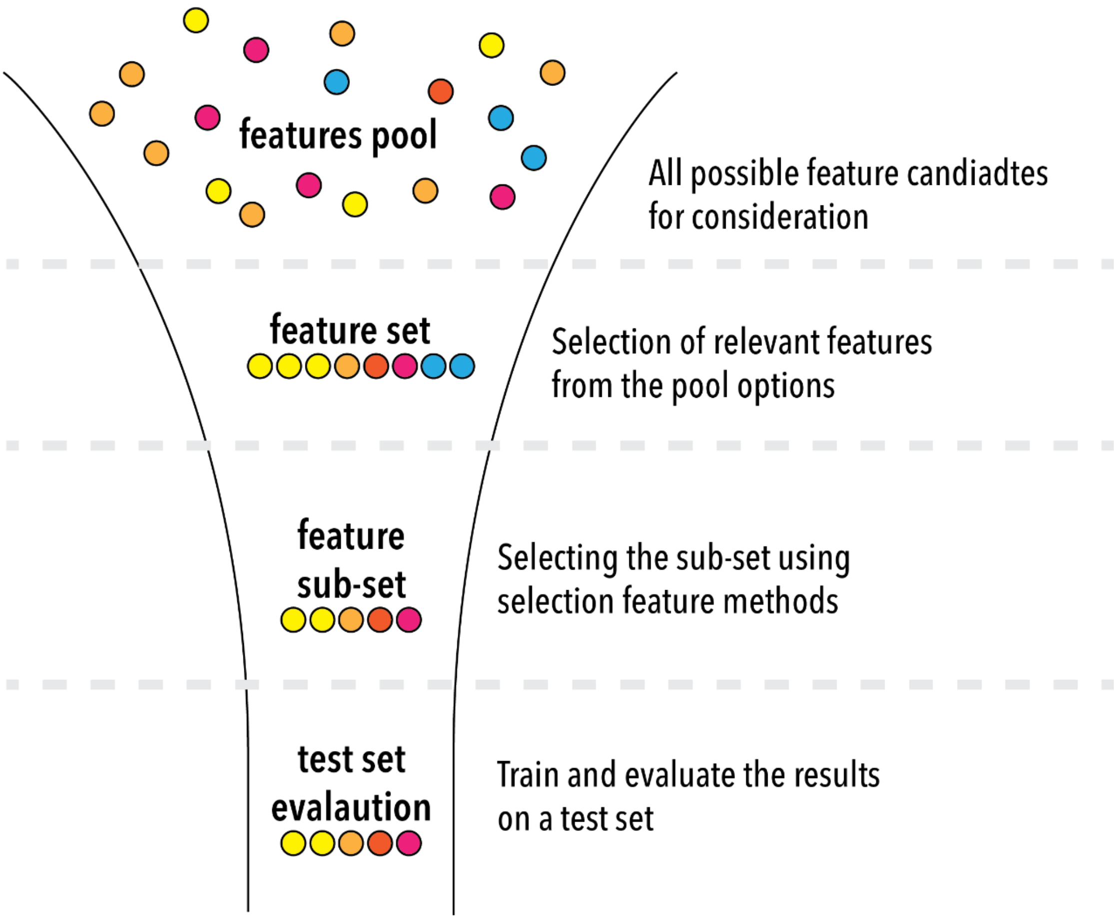


Figure 50: machine learning feature selection and testing pipeline.

5.2 Processing the Data for Testing

This section will detail the digital tools, data, and algorithms required to build a machine learning model for assessing wayfinding quality. The work will augment an existing floor plan geometry dataset assessment results and geometry features. A comprehensive pipeline is developed to perform assessment and extract geometric features. The initial iteration is focused on features that relate to the living room. Numeric tabular values are chosen for the format to enable a faster iteration process between the assessment algorithm and model tuning. Four key requirements were identified to build a basic AI model capable of predicting wayfinding quality based on floor plan geometry: data collection, data pre-processing, model building, and result evaluation.

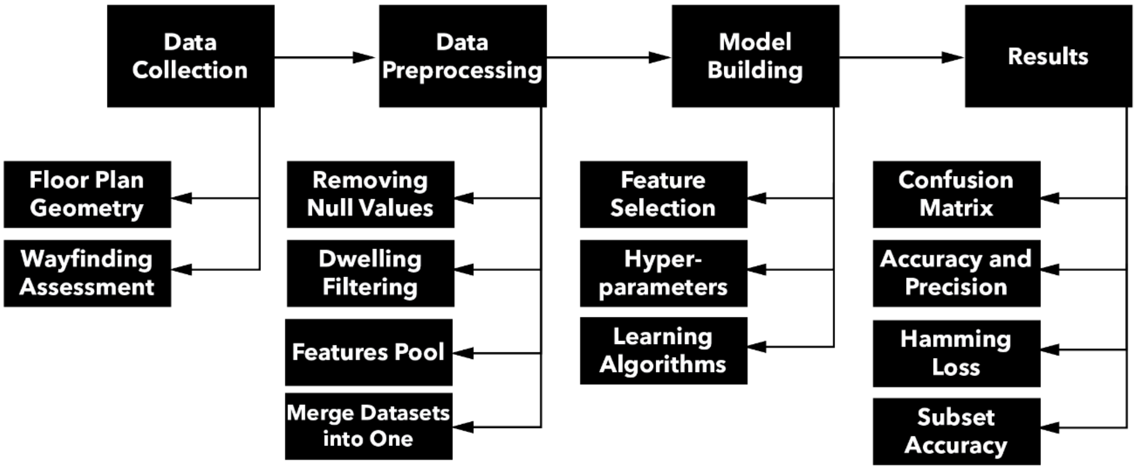


Figure 51: The overall process to building an AI model for assessing soft criteria related to dementia care, i.e. wayfinding quality.

5.2.1 The Model's Target Objective

The primary objective, also known as target variables, is to predict the wayfinding quality class for the living space.

The model's function was determined to predict the wayfinding quality of a floor layout based on building geometry information taken from isovist measurements of wayfinding quality indicators described in an earlier chapter. The AI model aims to predict wayfinding quality by correlating visual access data with extracted building geometry features. The goal at the final '*stage 4*' is to develop a machine capable of interpreting the wayfinding quality of an entire floor plan and providing individual assessments for each performance indicator to rank the overall quality of a floor plan based on the soft design criteria categories.

The scope of this thesis is completing stage 1, working towards building comprehensive pipeline for the wayfinding quality assessment model. Currently the model tests one performance indicator, 2_2 wayfinding quality indicator, which measures sightlines between living and kitchen, with an initial selection of feature pool.

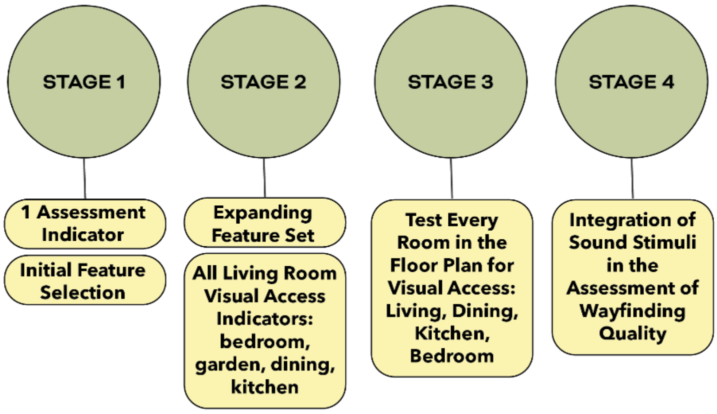


Figure 52: The model development's milestones for a comprehensive assessment of wayfinding quality.

In this project, a supervised learning method will be used to fit the data between wayfinding quality labels (target variables) and building geometry features (inputs). This method will allow us to correspond between the two variables, isovist measures extracted from the assessment results, and building geometry features. Wayfinding qualities are described as three discrete classes: 0, 1, and 2, thereby a multiclass classification problem will be used.

An initial training data of floor plan geometry was selected from the Swiss Dwellings dataset for its high quantity and ready-to-use quality for machine learning applications including simulation features. The floor plan was imported into Grasshopper and evaluated by the assessment algorithm which developed in this project to generate numeric value describing visual access of a space in relation to a different adjacent space. Combing both visual access values of different adjacent spaces (e.g. living and kitchen, living and bedroom, etc.), a room can be assigned a score based on the soft criteria described in an earlier chapter (e.g. autonomy, connection, accessibility). For building the proof-of-concept model, only 1 assessment indicator is used belonging to the 'connection' soft criteria.

The model's function is envisioned to take building geometry as input from the Swiss Dwellings dataset where an algorithm first extracts its features (i.e. through Grasshopper) then these features will be plugged into the model to provide assessment feedback on the wayfinding quality per each performance indicator as discrete classes:

2 being preferred
1 being sufficient
0 being insufficient

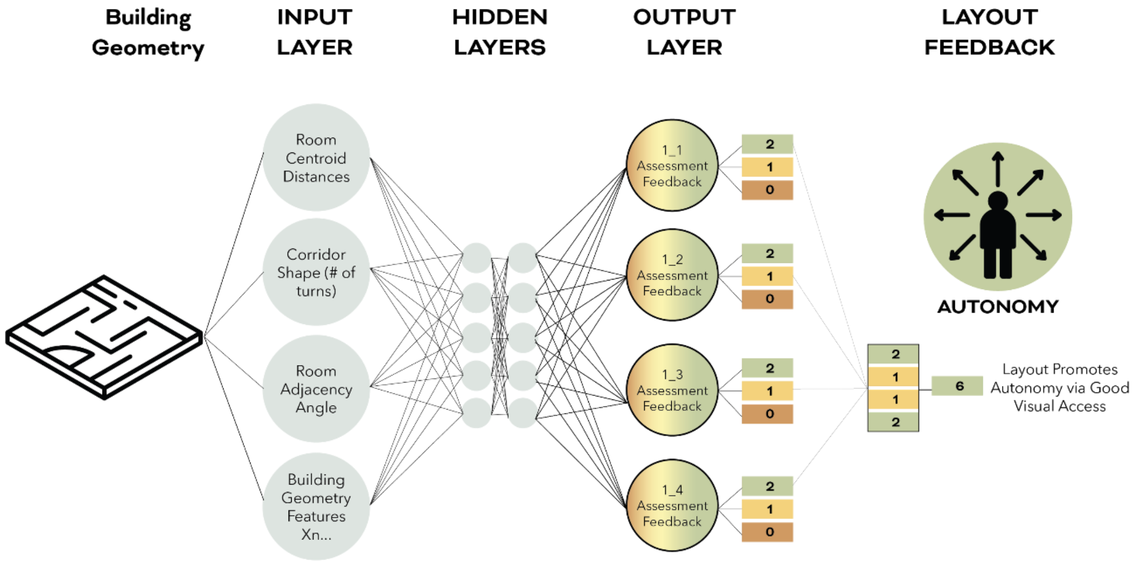


Figure 53: the final model will work by taking a building geometry of area boundaries, extract its features, input the features into the model, then receive assessment feedback on the wayfinding quality indicators.

The choice for neural network was largely decided based on the observed non-linear nature of the features. Another reason for this choice is to allow for scalability using the same model when increasing the data size of floor plans and increasingly complex feature sets with multiple assessment indicators.

5.2.2 Training Data: Swiss Dwellings

The process began with selecting a suitable dataset of floor plans that we can use for conducting the performance assessment. The first choice was to digitize floor plans of Dutch dementia care facilities form the literature (which add up to around 19 raster images containing information such as zone perimeter, walls, and door locations). The problem with this approach is the low quantity of the floor plans in addition to converting the low-quality raster images into vector-based format or tabular numerical value of the building geometry. The decision to choose the Swiss Dwelling dataset was made later on because of its high quality geometry, large quantity, and ready for application using minimal processing steps to get it ready.

The Swiss Dwellings dataset was discovered during the literature review phase of this thesis. It is a large dataset of apartment models accompanied with simulation results for the dwellings of geolocation-based features covering wide range of categories including natural light, centrality, viewshed, traffic noise, geometric analysis, and so on (Standfest et al., 2022). The dataset is publicly available on Zenondo, an open source library of datasets found online at https://zenodo.org/records/7070952. The dataset contains detailed data on over 42 thousand apartments, nearly a total of 242 thousand rooms in over 3000 buildings. The data is labelled using consistent formats for all important information needed to have such as room geometry, wall geometry, door geometry, window geometry, room functions, etc. The dataset was sourced through Archilyse AG, a software company based in Zürich specializing in the digitization and analysis of buildings, from their commercial clients.

Before we can use the dataset, a sub-selection of dwellings is needed to control the requirements needed for each floor layout. For example, the layout should be residential, should include key spaces that are taken into consideration for a layout's wayfinding quality while still manageable enough to be able to perform visual inspection when necessary. The dwellings should have more than 3 bedrooms minimum, single-story household, and contain a dining space and/or kitchen clearly defined as an area boundary. The earlier study on patient's satisfaction had great results with a data size of around 500 (Ali et al., 2022), therefore, the goal is to keep the dwelling samples around this size.

To select only the dwellings that can be used for the measurement procedures, these were the filter steps taken:

1. Single-story dwellings by filtering unit_id values that have multiple floor_id values
2. Has more 3 or more bedrooms by testing that unit_id contains corresponding two instances of 'bedroom' enitity_subtype
3. Has a room function "Kitchen" by testing that unit_id contains corresponding an instance of 'kitchen' unitity_subtype
4. ~~Has room function "Dining"~~ *(this has been removed due to the inconsistency of dining room designation which made the total dwellings count to less than 100 useful floor layouts)*

First, we isolate the floor plans for residential only:

```
residential_dataset = full_dataset[full_dataset['unit_usage'] == 'RESIDENTIAL']

Output: unit_id count = 46937
```

Figure 54: initial filtering for residential only

Then we select only single-story dwellings.

```
# Count the number of unique unit_ids per apartment_id
apartment_unit_counts = residential_dataset.groupby('apartment_id')['unit_id'].nunique()

# Get the apartment_ids with only one unique unit_id (single-story apartments)
single_story_apartments = apartment_unit_counts[apartment_unit_counts == 1].index

# Filter rows to include only single-story apartments
df_single_story = residential_dataset[residential_dataset['apartment_id'].isin(single_story_apartments)]

# Use nunique() method to get the number of unique items per column
unique_counts = df_single_story.nunique()

Output: unit_id count = 43192
```

Figure 55: checking for dwellings that contain one apartment_id per unit_id

It was later observed that the labelling for spaces are not standardized across the entire dataset. Therefore, an initial label standardization has been done by passing through all different found labels to uniform labels.

```
# Create a list of variations of living room labels
living_room_labels = ['LIVING_ROOM','LIVING_DINING']
# dining_labels = ['KITCHEN_DINING']
bedroom_labels = ['STUDIO']
other_labels = ['STORELIVING','STOREBEDBEDROOM','STOREBEDROOM','STOREROOM']
bath_labels = ['BATHROOM']
outdoor_labels = ['TERRACE','BALCONY','OUTDOOR_VOID','LOGGIA','GARDEN']

# Define the required entity_subtypes
required_entity_subtypes = ['LIVING', 'BEDROOM', 'KITCHEN', 'CORRIDOR', 'BATH']

Output: unit_id 9270
```

Figure 56: then a filter process was performed to select building geometry that contain these functions: living, bedroom, kitchen, corridor, bath. Outputting 9270 dwellings.

Then, we initiate another filtering process to select dwellings that contain 3 or more bedroom instances per one unique unit_id.

```
# Selecting unique unit_id samples containing more than 3 bedrooms
bedroom_data = df[df['entity_subtype'] == 'BEDROOM'].groupby('unit_id')
bedroom_counts = bedroom_data[entity_subtype].count()
unit_ids_with_enough_bedrooms = bedroom_counts[bedroom_counts > 3].index
filtered_df = df[df['unit_id'].isin(unit_ids_with_enough_bedrooms)]

Output: unit_id 593
```

Figure 57: then a filter process was performed to select building geometry that contain these functions: living, bedroom, kitchen, corridor, bath. Outputting 9270 dwellings. Outputting 593 dwellings.

Finally, we select a sample size of 500 dwellings to build our machine learning model on. A test sample of 93 dwellings is also put aside for testing the final model.

```
# Selecting a small subset of the samples
unique_unit_ids = df['unit_id'].unique()
top_500_unit_ids = unique_unit_ids[:500]
filtered_df = df[df['unit_id'].isin(top_500_unit_ids)]
```

Figure 58: filtering method to select the top 500 unique unit_ids.

However, during the physical inspection phase, it has been observed that there are a combination of building geometry that has been corrupted (either an error in the existing dataset or an error from the Grasshopper import operation) but more critically too many dwellings that are perfect replicas of one another. The process of manual filtering by visually inspecting each dwelling to remove any duplicates from the selected sample was completed. In the end, this process yielded 268 unique dwellings. Further down the line, it was discovered some living rooms had open polygons which could not be handled in the Grasshopper code, reducing the total count of dwellings to 256.

```
# Filtering the DataFrame
filtered_geo = geo_500[~geo_500['unit_id'].isin(cull_list)]

unique_counts = filtered_geo.nunique()
print(unique_counts)

apartment_id        268
site_id             102
building_id         138
plan_id             192
floor_id            204
unit_id             268
area_id            3736
unit_usage            1
entity_type           4
entity_subtype       28
geometry          24040
elevation            83
height               42
dtype: int64
```

Figure 59: final filtering procedure yielded 268 dwellings. See Appendix 6 for thumbnails of the sample.

Figure 60: a scatter plot showing the living room area compared to the number of bedrooms available in a single-story dwelling.

5.2.3 Thresholds for Visual Access Measure

The classification of wayfinding quality describes the visual access measurement by defining the threshold for the assessment, and in this exercise, it was strictly defined for the purpose of creating diverse results of all three classes to avoid the issue of imbalanced class labels. This step was qualitatively done and the threshold for the model has been determined to allow for diverse results due to the restricted size of our dataset. But in ideal case-scenarios, the thresholds are determined by the subject-matter expert in wayfinding compliance with dementia design principles, which will therefore surely require a much larger dataset of floor plan subdue potentially imbalanced labels.

The floor plans are prepared in a digital environment (Rhino + Grasshopper) to prepare for the performance assessment. The digital algorithm, expressed in a Grasshopper definition, is intended to import a subset of apartments from the dataset that systematically perform and record the assessment results of each layout for all performance indicators of one group, i.e. wayfinding quality score measured from visual access results taken from different locations in the dwelling. The data is then recorded, alongside with the unit_id associated with each recording, to later amalgamate generated data back to the Swiss Dwelling subset of apartments using Pandas merge operation in Python.

The threshold have been set as follows:

```
bin_ranges = [
    (0.0, 0.35, 'insufficient'),
    (.35, 0.75, 'sufficient'),
    (0.75, 1, 'preferred')]
```

Figure 61: the following threshold of visual access settings allow for the most variability of all three classes.

From the assessment algorithm in grasshopper, the settings used ensured it gave variable results across all 268 floor plans. The settings are as follows:

1. Test point spacing = 1 meter
2. Minimum distance from the perimeter wall = 0.75 meters
3. Isovist length = 12 meters
4. Radial isovist count = 24 rays
5. Obstacles/barriers = walls only (doors assumed to contain glazed panel with privacy shutters)

Note: with the current understanding of visual access for DDP, there are no thresholds set by experts in this subject. More work on this is needed to validate useful thresholds especially when considering people with varying dementia stages. For now, all bins will be created to allow for balanced distribution of classes for all output classes.

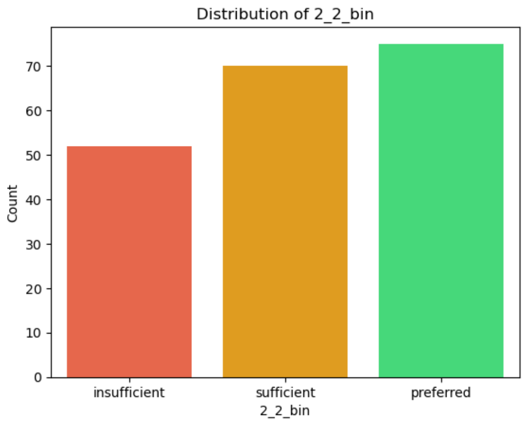


Figure 62: distribution has now improved from being skewed to preferred and low diversity to almost evenly distributed results.

5.2.4 Building Geometry Feature Extraction

The floor plan from each dwelling also undergoes the procedure of feature extraction by taking the raw geometry information and converting them into numeric values that is stored and passed on as an excel or CSV file to store alongside their corresponding unit_id. This step is useful for iterating through different features that can be used for testing the machine learning model to see which allow for digital pipeline from Grasshopper environment into Python for further processing and combining the dataset. One key advantage for processing our own building geometry for feature extraction is that we can use the same algorithm for any floor plans whether it is from the Swiss Dwellings set or elsewhere.

Feature Set 2		
Feature Name	**Feature Categpry**	**Feature Description**
X1	Distance-based features	AVERAGE DISTANCE BETWEEN LIVING AND ALL DOORS
X2		AVERAGE ANGLE BETWEEN LIVING AND ALL DOORS
X3		AVERAGE DISTANCE BETWEEN LIVING AND KITCHEN
X4	Wall-to-Opening Ratio	WALL LENGTH / ZONE LENGTH
X5	Area Ratios	LIVING AREA / KITCHEN AREA
X6		LIVING AREA / FLOOR PLAN AREA"
X7		LIVING AREA / CORRIDOR AREA
X8	Nearest Distance	AVERAGE DISTANCE TO NEAREST TOILET
X9	Shape Complexity	CORRIDOR MOMENTS OF DECISION
X10	Perimeter Length	LIVING PERIMETER LENGTH
X11		KITCHEN PERIMETER LENGTH
X12	Compactness	LIVING COMPACTNESS
X13		KITCHEN COMPACTNESS

Figure 63: a list of potential features for testing developed during this thesis.

In addition to the geometry features extracted via Grasshopper, the Swiss Dwellings simulation file contain many numeric values which includes viewshed, natural light, traffic noise, etc. Some of the most relevant features that may be of interest are the ones that describe spatial adjacencies and relationships, such as centrality. Moreover, there is an isovist view properties that of particular interest to investigate. Other geometry features that are also interesting for investigation describe the layout such as compactness and perimeter properties. The simulation file from the Swiss Dwellings dataset will also be tested. One downside of these simulation features is that it is not clear how it was done and no easy way to re-produce it for floor plans outside of the Swiss Dwellings dataset. Due to time constraints, only a small fragment of this feature pool was tested.

layout_compactness
layout_mean_walllengths
layout_std_walllengths
layout_number_of_doors
layout_has_entrance_door
layout_perimeter
layout_door_perimeter
layout_connects_to_private_outdoor
layout_biggest_rectangle_length
layout_biggest_rectangle_width
view_isovist_max
view_isovist_mean
view_isovist_median
view_isovist_min
view_isovist_p20
view_isovist_p80
view_isovist_stddev
connectivity_eigen_centrality_max
connectivity_eigen_centrality_mean
connectivity_eigen_centrality_median
connectivity_eigen_centrality_min
connectivity_eigen_centrality_p20
connectivity_eigen_centrality_p80
connectivity_eigen_centrality_stddev
connectivity_entrance_door_distance_max
connectivity_entrance_door_distance_mean
connectivity_entrance_door_distance_median
connectivity_entrance_door_distance_min
connectivity_entrance_door_distance_p20
connectivity_entrance_door_distance_p80
connectivity_entrance_door_distance_stddev
connectivity_betweenness_centrality_max
connectivity_betweenness_centrality_mean
connectivity_betweenness_centrality_median
connectivity_betweenness_centrality_min
connectivity_betweenness_centrality_p20
connectivity_betweenness_centrality_p80
connectivity_betweenness_centrality_stddev
connectivity_closeness_centrality_max
connectivity_closeness_centrality_mean
connectivity_closeness_centrality_median
connectivity_closeness_centrality_min
connectivity_closeness_centrality_p20
connectivity_closeness_centrality_p80
connectivity_closeness_centrality_stddev
connectivity_bathroom_distance_max
connectivity_bathroom_distance_mean
connectivity_bathroom_distance_median
connectivity_bathroom_distance_min
connectivity_bathroom_distance_p20
connectivity_bathroom_distance_p80
connectivity_bathroom_distance_stddev
connectivity_kitchen_distance_max
connectivity_kitchen_distance_mean
connectivity_kitchen_distance_median
connectivity_kitchen_distance_min
connectivity_kitchen_distance_p20
connectivity_kitchen_distance_p80
connectivity_kitchen_distance_stddev

Figure 64: an overview of the most suitable features based on visual inspection of the column names for the Swiss Dwelling simulation dataset.

5.2.4 Final Training Set

Ultimately the final dataset will contain the floor plan data from the Swiss Dwellings, performance assessment values, and building geometry features in a single tabular numeric file. The numeric format is easy to handle and is shown to be an advantage for further machine learning optimization that can get computationally expensive, affording the opportunity to quickly iterate between features and hyperparameter tuning. The total number of dwellings is 256 after the removal of invalid geometries.

tity_subty	geometry	elevation	height	LIV_KIT	LIV_BED1	LIV_BED2	LIV_BED3	LIV_BED4	LIV_BED5	LIV_BED6	# OF BEDS	LIV_BATH1	LIV_BATH2	LIV_BATH3	# OF BATH	invalid_geometry	LIV_KIT_bin	LIV_KIT_bin_mapped	layout_compactness	layout_std_walllengths	out_perim	_door_per	_open_per	number_o	rance_doo	rance_doo
LIVING	POLYGON	8.7	2.6	0.375	2.25	0	0	0	0	0	3	0	0	0	2	Unit_id 53095: VALID GEOMETRY	1_sufficient	1	0.643464496	1.576665561	25.54875	3.995188	0	3	13.75	10.52903
LIVING	POLYGON	0	2.6	0.125	0	0	0	0	0	0	3	0	0	0	2	Unit_id 134183: VALID GEOMETRY	0_insufficient	0	0.723587429	1.457574133	19.90456	1.39815	0	2	9.25	6.101064
LIVING	POLYGON	2.9	2.6	0	0	0	0	0	0	0	3	0.047619	0	0	2	Unit_id 134200: VALID GEOMETRY	0_insufficient	0	0.666554319	2.127253425	26.89863	4.027087	0	3	11.75	8.532885
LIVING	POLYGON	8.7	2.6	1	0.0625	0.4375	0	0	0	0	4	0	0	0	2	Unit_id 130199: VALID GEOMETRY	2_preferred	2	0.610187	1.878597575	24.98365	0	0	0	8.75	6.072581
LIVING	POLYGON	8.7	2.6	0.833333	0	0	0	0	0	0	4	0	0	0	2	Unit_id 130203: VALID GEOMETRY	2_preferred	2	0.60659885	1.793215564	24.55089	0	0	0	9.25	5.891527
LIVING	POLYGON	5.8	2.6	0.56	1.44	0.08	0.12	0	0	0	3	0.12	0.12	0	3	Unit_id 130516: VALID GEOMETRY	1_sufficient	1	0.772231975	2.509872894	26.12231	4.133999	0	4	13	9.180323
LIVING	POLYGON	2.9	2.6	0.68	0	0	0.04	0.48	0	0	4	0	0	0	3	Unit_id 130521: VALID GEOMETRY	1_sufficient	1	0.78061398	2.555047733	24.59911	3.119844	0	3	12.5	10.04405
LIVING	POLYGON	8.7	2.6	1	1.426471	0.088235	0	0	0	0	2	0.191176	0.073529	0	2	Unit_id 130525: VALID GEOMETRY	2_preferred	2	0.425760435	3.610247649	53.98915	0	0	0	12.5	6.722222
LIVING	POLYGON	8.7	2.6	1	0	0	0	0	0	0	3	0	1	0	2	Unit_id 134003: VALID GEOMETRY	2_preferred	2	0.682780994	1.1061826	17.00238	1.644125	0	2	5.75	3.262842
LIVING	POLYGON	8.7	2.6	1	0	0	0.125	0	0	0	3	0.875	0.25	0	2	Unit_id 134011: VALID GEOMETRY	2_preferred	2	0.684144319	1.105296443	16.96213	1.636137	0	2	6.5	3.702632
LIVING	POLYGON	5.8	2.6	1	0	0	0	0	0	0	3	1	0.6	0	2	Unit_id 134041: VALID GEOMETRY	2_preferred	2	0.684143804	1.105022041	16.96213	1.636137	0	2	5.5	3.145051
LIVING	POLYGON	5.8	2.6	1	0	0	0	0	0	0	3	0.833333	0	0	2	Unit_id 134046: VALID GEOMETRY	2_preferred	2	0.682865679	1.111068188	17.0045	1.644125	0	2	6.5	3.612069
LIVING	POLYGON	11.6	2.6	0.647059	1	0.764706	0	0	0	0	3	0	0	0	2	Unit_id 94441: VALID GEOMETRY	1_sufficient	1	0.558655248	1.463136279	27.64898	7.598897	0	6	8	4.69059
LIVING	POLYGON	0	2.6	0	0.3	0	0	0	0	0	4	0	0.2	0	2	Unit_id 133584: VALID GEOMETRY	0_insufficient	0	0.704087758	2.277390562	20.87062	1.78109	0	2	12.25	10.42984
LIVING	POLYGON	0	2.6	0.5	0	0	0	0	0	0	5	0	0	0	2	Unit_id 133597: VALID GEOMETRY	1_sufficient	1	0.722890651	1.434061422	20.41833	2.663141	0	4	12.25	10.51749
LIVING	POLYGON	8.7	2.6	0.444444	0	0	0	0	0	0	4	0	0	0	3	Unit_id 145636: VALID GEOMETRY	1_sufficient	1	0.782946337	1.955538467	19.55583	0	0	2	8.5	5.297727
LIVING	POLYGON	6.22	2.7	1	0	0	0	0.3	0	0	4	0	0	0	3	Unit_id 160793: VALID GEOMETRY	2_preferred	2	0.727124236	1.80533174	21.273	3.435769	0	2	11.5	7.676136
LIVING	POLYGON	9.22	2.7	1	0	0	0	0	0	0	4	0	0	0	3	Unit_id 160814: VALID GEOMETRY	2_preferred	2	0.732939976	1.600225982	21.30339	3.464772	0	2	10.25	6.891616
LIVING	POLYGON	21.82	2.9	1	0	0	0	0	0	0	1	0	0	0	2	Unit_id 160838: VALID GEOMETRY	2_preferred	2	0.689174401	1.848244465	23.21749	6.326618	0	2	11.25	7.464801
LIVING	POLYGON	3.22	2.7	1	0	0.133333	0	0	0	0	4	0	0	0	3	Unit_id 160822: VALID GEOMETRY	2_preferred	2	0.733226223	1.652073918	21.28024	3.445945	0	2	10.25	6.905804
LIVING	POLYGON	3.22	2.7	1	0	0.3	0	0	0	0	4	0	0	0	3	Unit_id 160825: VALID GEOMETRY	2_preferred	2	0.728152956	1.655203846	21.31146	3.435893	0	2	11.5	7.757216
LIVING	POLYGON	11.6	2.6	0.846154	0	0	0	0	0	0	3	0.076923	0	0	2	Unit_id 103667: VALID GEOMETRY	2_preferred	2	0.498813561	1.244509042	28.26784	2.208217	0	3	16.75	12.05522
LIVING	POLYGON	0	2.6	0.133333	0	0	0	0	0	0	3	0	0	0	2	Unit_id 103746: VALID GEOMETRY	0_insufficient	0	0.599351889	1.373614081	24.38581	0.948222	0	1	13.5	10.40779
LIVING	POLYGON	2.9	2.6	0.166667	0.333333	0	0	0	0	0	3	0.25	0	0	2	Unit_id 103754: VALID GEOMETRY	0_insufficient	0	0.552436991	1.266711025	25.24726	0.950716	0	1	13.5	10.39904
LIVING	POLYGON	5.8	2.6	0.166667	0	0	0	0	0	0	3	0	0.166667	0	2	Unit_id 103767: VALID GEOMETRY	0_insufficient	0	0.551865061	1.220714616	24.96885	0.937741	0	1	13.5	10.30128
LIVING	POLYGON	11.6	2.6	0.529412	0.352941	0.176471	0	0	0	0	3	0	0.235294	0	2	Unit_id 103777: VALID GEOMETRY	1_sufficient	1	0.503099484	1.209955975	28.34964	2.45433	0	3	997	997
LIVING	POLYGON	11.6	2.6	0.285714	0.5	0	0	0	0	0	3	0.071429	0.428571	0	2	Unit_id 103780: VALID GEOMETRY	0_insufficient	0	0.484952834	1.29816641	30.39703	2.976668	0	4	17	13.58546
LIVING	POLYGON	8.7	2.6	0.25	0	0	0	0	0	0	3	0	0.25	0	2	Unit_id 103789: VALID GEOMETRY	0_insufficient	0	0.552434479	1.247438688	24.86314	0.936286	0	1	13.25	10.24152
LIVING	POLYGON	11.6	2.6	0.944444	0.222222	0.944444	0	0	0	0	3	0	0	0	4	Unit_id 135979: VALID GEOMETRY	2_preferred	2	0.391439905	2.805489592	35.53013	1.8	0	4	17	11.26992
LIVING	POLYGON	11.6	2.6	1	4.4	0	0	0	0	0	2	0	0.4	0	3	Unit_id 135982: VALID GEOMETRY	2_preferred	2	0.426838241	2.253651237	28.10439	3.842532	0	4	13	9.129555
LIVING	POLYGON	0	2.6	0.958333	0	0	0	0	0	0	2	0	0	0	2	Unit_id 137426: VALID GEOMETRY	2_preferred	2	0.722772619	1.315514605	25.87015	2.78078	0	2	7.75	4.89595
LIVING	POLYGON	2.9	2.6	0.727273	0.545455	0	0	0	0	0	3	0	0	0	3	Unit_id 137428: VALID GEOMETRY	1_sufficient	1	0.738427683	1.74728535	26.05481	2.061618	0	2	855.5	855.5
LIVING	POLYGON	5.8	2.6	0	0.368421	0	0	0	0	0	3	0	0	0	3	Unit_id 137435: VALID GEOMETRY	0_insufficient	0	0.728142088	2.045479553	25.45741	1.970291	0	2	12.5	8.517518
LIVING	POLYGON	2.9	2.6	1	0.142857	0.285714	0.142857	0	0	0	4	0	0	0	2	Unit_id 144220: VALID GEOMETRY	2_preferred	2	0.693669617	1.092729236	21.74349	2.425132	0	2	9.5	5.302192
LIVING	POLYGON	0	2.6	0.9	0	0	0	0.2	0	0	4	0	0	0	2	Unit_id 144228: VALID GEOMETRY	2_preferred	2	0.692278022	1.231571867	22.25756	2.470907	0	2	8	4.56994
LIVING	POLYGON	0	2.6	1	1.733333	0	0	0.066667	0	0	4	0	0	0	2	Unit_id 144229: VALID GEOMETRY	2_preferred	2	0.694656131	1.262458888	22.22016	2.470907	0	2	9.5	5.219185
LIVING	POLYGON	0	2.6	1	0.714286	0.571429	0	0.071429	0	0	4	0	0	0	2	Unit_id 144237: VALID GEOMETRY	2_preferred	2	0.694979913	1.238627139	22.12517	2.449409	0	2	8.25	4.721386
LIVING	POLYGON	0	2.6	1	1.1	0	0	0.5	0	0	4	0	0	0	2	Unit_id 144238: VALID GEOMETRY	2_preferred	2	0.693840749	1.200699135	22.12914	2.449409	0	2	9.5	5.137275
LIVING	POLYGON	2.9	2.6	1	0.166667	0	0.583333	0.75	0	0	4	0	0	0	2	Unit_id 144239: VALID GEOMETRY	2_preferred	2	0.694499372	1.237901173	22.1283	2.449435	0	2	8	4.635859
LIVING	POLYGON	2.9	2.6	0.933333	0.933333	0.133333	0	0.066667	0	0	4	0	0	0	2	Unit_id 144240: VALID GEOMETRY	2_preferred	2	0.693498813	1.20024365	22.13041	2.449435	0	2	9.5	5.147796
LIVING	POLYGON	5.8	2.6	0.923077	0.461538	0.538462	0	0.846154	0	0	4	0	0	0	2	Unit_id 144247: VALID GEOMETRY	2_preferred	2	0.690993654	1.237102897	22.19794	2.44867	0	2	8.25	4.673154
LIVING	POLYGON	5.8	2.6	1	1.8	0.066667	0.333333	0	0	0	4	0	0	0	2	Unit_id 144248: VALID GEOMETRY	2_preferred	2	0.693498773	1.199868266	22.12349	2.44867	0	2	9.5	5.096806

```
[(0, 'apartment_id'), (1, 'site_id'), (2, 'building_id'), (3, 'plan_id'), (4, 'floor_id'), (5, 'unit_id'), (6, 'area_id'), (7, 'unit_usage'), (8, 'entity_type'),
(9, 'entity_subtype'), (10, 'geometry'), (11, 'elevation'), (12, 'height'), (13, 'LIV_KIT'), (14, 'LIV_BED1'), (15, 'LIV_BED2'), (16, 'LIV_BED3'), (17,
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'connectivity_kitchen_distance_max'), (63, 'connectivity_kitchen_distance_mean'), (64, 'connectivity_kitchen_distance_median'), (65,
'connectivity_kitchen_distance_min'), (66, 'connectivity_kitchen_distance_p20'), (67, 'connectivity_kitchen_distance_p80'), (68,
'connectivity_kitchen_distance_stddev'), (69, 'layout_biggest_rectangle_length'), (70, 'layout_biggest_rectangle_width'), (71, 'LIV_BATH_bin'), (72,
'LIV_BATH_bin_mapped'), (73, 'LIV_BED_count'), (74, 'LIV_BED_ratio'), (75, 'LIV_BED_bin')]
```

Figure 65: The complete dataset of living room wayfinding quality for based on the geometry from the Swiss Dwelling set. 256 unique living rooms and 76 columns. The colored group of features on the left is the Swiss Dwelling geometry, the red in the middle is the assessment results, the green/blue on the right are features from the simulation set found in the Swiss Dwellings.

5.3 Exploratory Data Analysis

5.3.1 Building Geometry Features from Grasshopper

The distribution of labels and their correlation with features is plotted using histograms and scatter plots. From these plots we can get an understanding of how the features are distributed to look for any trends in our data and the type of relationship the features have to the target variable (2_2 wayfinding quality from living to kitchen). This step give us an idea on the structure of the data we are working with to make better decisions on which features to start testing next. For example, a feature that have a distinct boundary or clear relationship with the target variable may be more useful to start with than features that don't have clear relationships or clear trendlines. Examining the features from Grasshopper, we can observe on the histogram that the distribution of labels is not clearly distinguished from one another. This can mean that the machine learning model could have a difficult time predicting the target variable. We can observe there is a weak trendline for feature X6 where the lower the value the likely it is a 'preferred' class. X1 has a concentration of labels for insufficient shown in its histogram which might offer some advantage in identifying insufficient labels, however, the potential advantage is limited due to the significant overlap in X1 values across all class as seen also in the KDE plot which confirms the concentration of labels of insufficient mostly overlapping with other class labels.

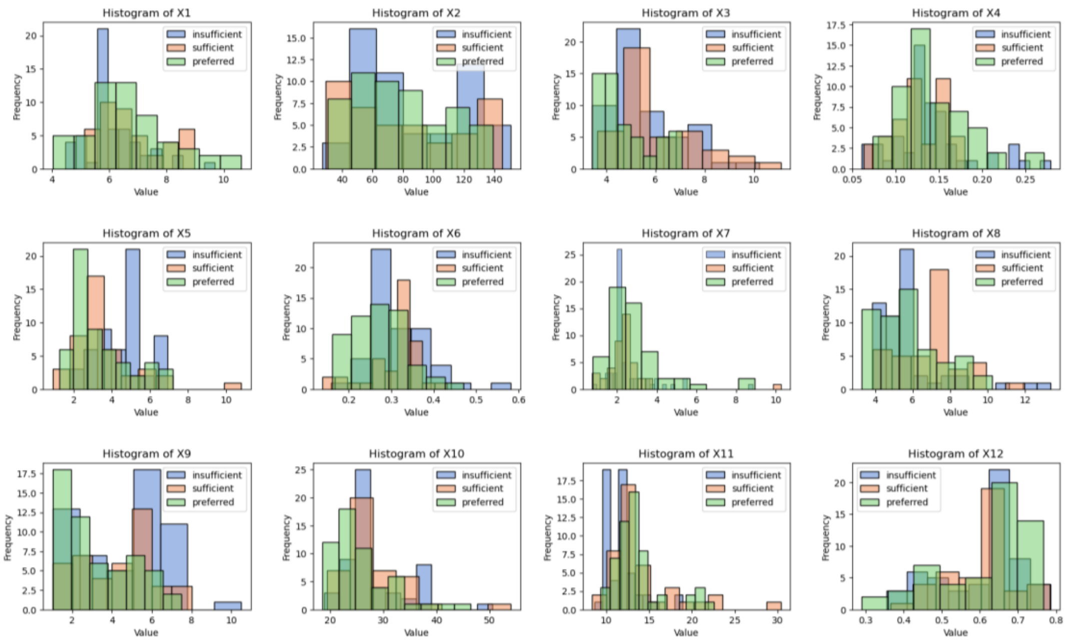


Figure 66: histogram plot for features extracted from Grasshopper.

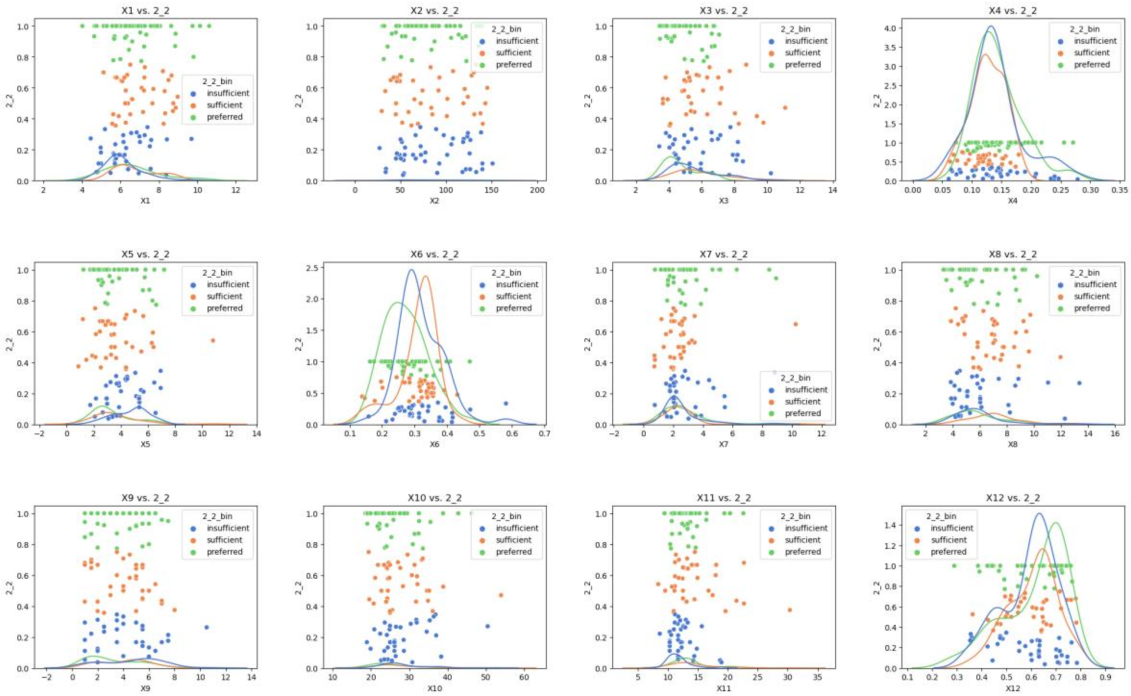


Figure 67: scatterplot with KDE curve overlaid for features extracted from Grasshopper.

5.3.2 Simulation Results from Swiss Dwelling Dataset

While there are not dominant trends in this feature set either, we can see a clearer trend for connectivity_kitchen_distance_p20 where the lower its value the more likely it is labeled as sufficient. Overall kitchen distances seem to be a likely predictor to target variable categories related to assessment indicator 2_2.

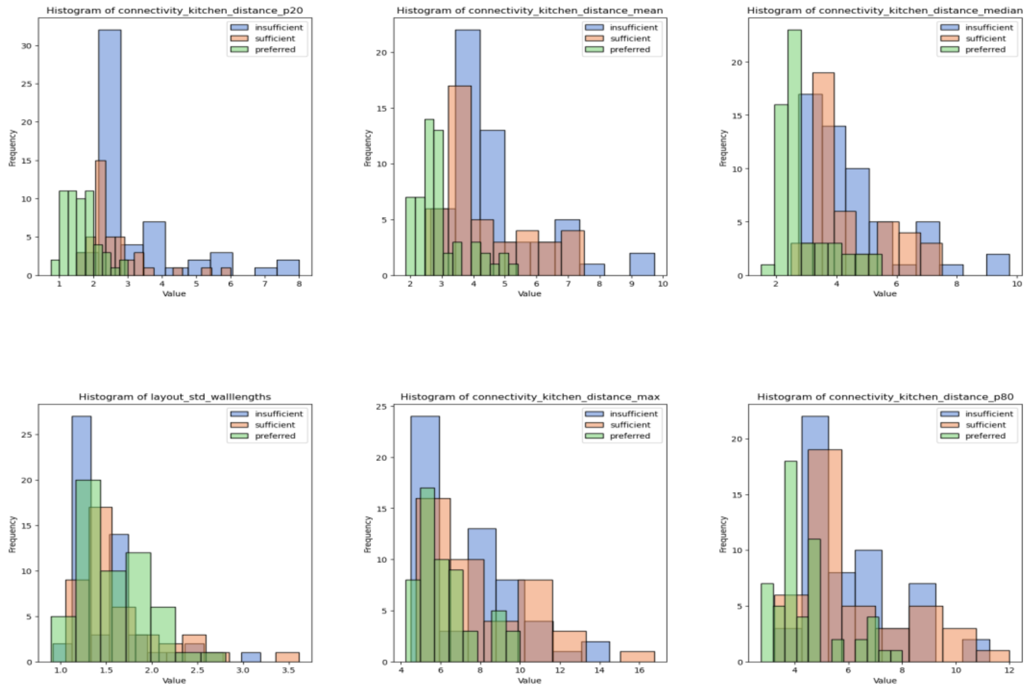


Figure 68: histogram plot for features extracted from Swiss Dwellings simulation.

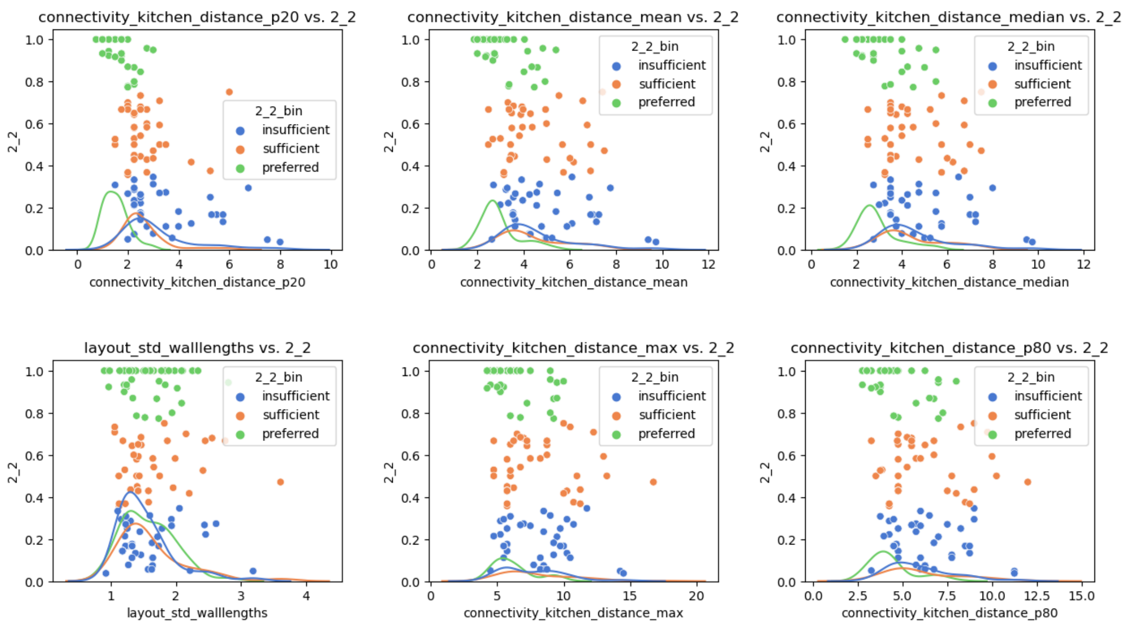


Figure 69: scatterplot with KDE curve overlaid for features from Swiss Dwellings simulation.

5.4 Observations on the Data

Undergoing this data analysis step for the features already identified some architectural means that are working well with satisfying the target objective of wayfinding quality from living to kitchen. However not very strong, there is a trend in the features describing distance between living room to dining room, for instance. At a glance, the features seem to not correlate well with the target variable which could be for multiple reasons. One being is that the Swiss Dwellings floor plan sample is too similar despite my best efforts to manually remove duplicates from the set (starting from 500 down to 256 in this iteration of data analysis). Another reason might be that the features themselves may not be the best indicator for wayfinding quality, and that more needs to be re-examined. Specifically more features need to be added that describe the conditions of the walls since it has a direct effect on visual access. Moreover, it is worth noting that the Swiss Dwellings are very unique in their own way and that testing it on a different typology of homes may not work due to the differences in the typology. Therefore, an even larger sample with more diversity is without a doubt the most impactful way to extract better features for the machine learning model to base its prediction on.

5.5 Conclusion

With the feature pool selection, the next chapter will document the process and results for building the first machine learning model prototype. The features will be put to the test using a neural network model architecture. Our labelled training dataset is stored with 256 unique dwellings that will undergo several steps for testing and improving the predictive abilities of the machine learning model. In principle, the outcome of the model will be able to take geometry of floor plans as inputs, process it to extract building features, pass it through the model, and provide assessment results on wayfinding quality with accuracy.

6 Machine Learning Model Results

6.1 Machine Learning Workflow

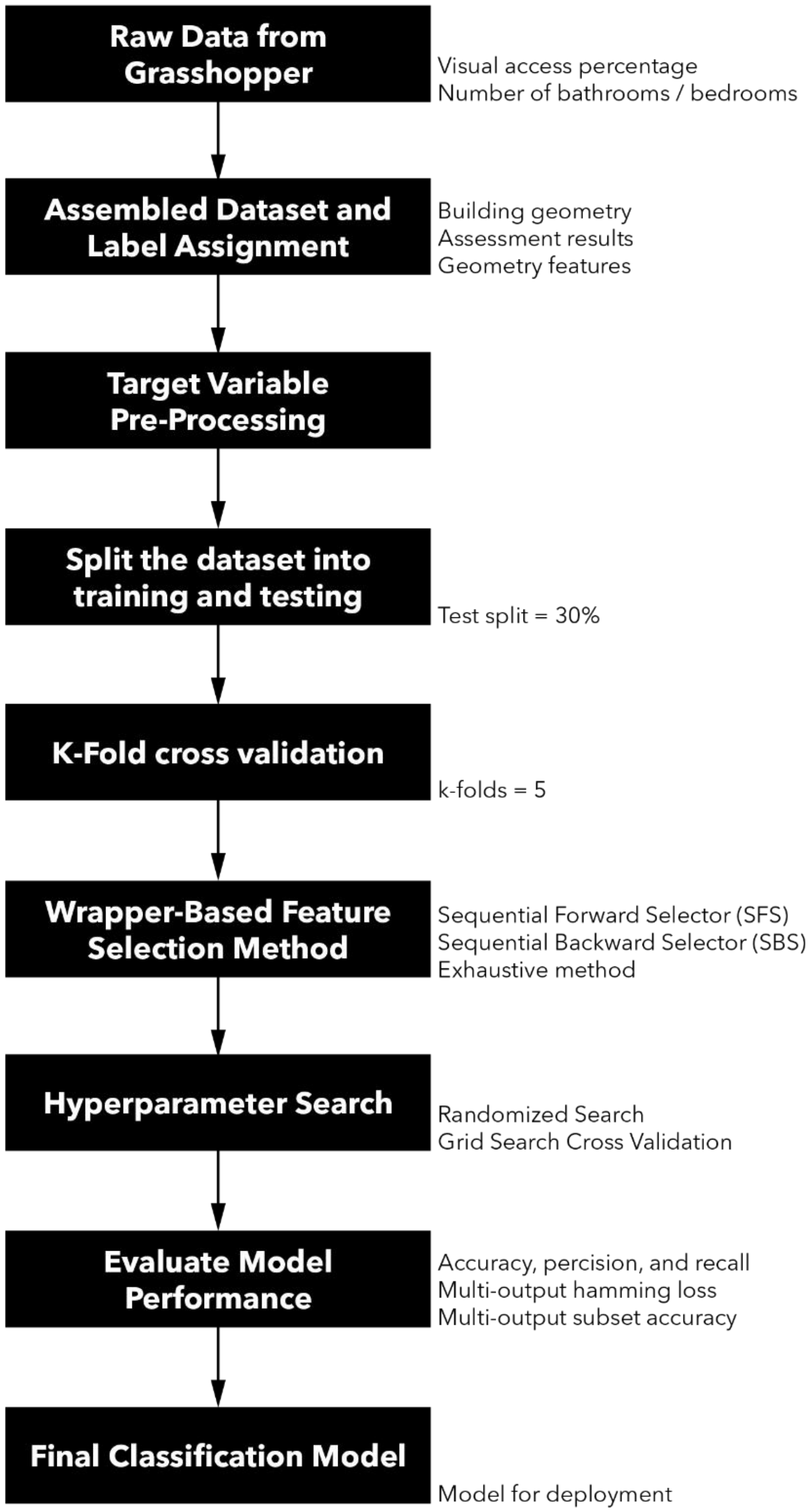


Figure 70: Workflow for determining the most suitable feature sets and hyperparameter settings.

At this step, we will take the data for visual access generated in Grasshopper and process it to perform machine learning operations. The setup includes the following:

Assigning Label Bins: Also known as creating 'bins' from the visual access data retrieved from Grasshopper to classify them based on the quality of the visual access.

Features Pool: First, we select all possible features available at this stage for consideration. In this case, we have features from the Swiss Dwellings dataset for examination. This step includes the removal of null, NaN, values from the code.

Multi-Output Evaluation Metrics: Guided by the SK Learn documentation and the literature, we set up additional metrics to evaluate multi-output model, i.e. models that predict visual access from the living room to multiple spaces.

Sequential Feature Selector: In this step, we perform a wrap-based filter method for feature selection utilizing both backward and forward sequential selection. An additional exhaustive search method on a smaller subset of features is used to plot the performance of all possible combinations to select the most suitable feature subset.

Hyperparameter Tuning: Using both Random Forest and Neural Network model architectures, we perform hyperparameter tuning to select the most suitable combination of model settings.

Evaluation: Finally, we evaluate the model using a confusion matrix, precision metrics, hamming loss, and subset accuracy to give us an idea of the performance of the model. The goal is for a model to be able to generalize on the test set of floor plans based on multiple sightline data from the living room to multiple spaces.

6.1.1 Assigning Label Bins

In this notebook, we have several assessment indicator to measure the sightlines between living room towards the kitchen, bathrooms, and bedrooms. In this notebook, a bin is intended to give us diverse distribution across all possible classes. In the instance of the kitchen, the bin range is defined to give us balanced classes. In the case of the bathroom, the rule is if any bathroom is visible, it gets one of two classes whether it is sufficient (visible from any point in the living room) or insufficient which is not visible from any point in the living room. The bedroom sightlines has been excluded from the rest of the code, but the bin process here was testing the visibility to all bedrooms, dividing the visibility by number of bedrooms in the household, to get a ratio for visible bedrooms from the living room which is a broad visual access quality to all bedrooms.

Below is the code to look at all visual sightline data from living to kitchen, and whenever any columns is 0, i.e. no sightlines created, it gets insufficient class, otherwise it is sufficient:

```
training_df['LIV_BATH_bin'] = training_df[['LIV_BATH1',
'LIV_BATH2']].max(axis=1).apply(lambda x: '0_insufficient' if x == 0 else
'1_sufficient').astype(str)
```

The bedroom sightline data is processed in multiple steps:

1. binning the bedroom sightlines have a greater value than 0:

```
training_df['LIV_BED_count'] = training_df[['LIV_BED1', 'LIV_BED2', 'LIV_BED3', 'LIV_BED4',
'LIV_BED5', 'LIV_BED6']].apply(lambda row: (row > 0).sum(), axis=1)
```

2. Calculate the ratio of bedrooms that have value greater than 0:

```
training_df['LIV_BED_ratio'] = training_df['LIV_BED_count'] / training_df['# OF BEDS']
```

3. Assign the binning ratio to allow for even distribution among the classes:

```
def classify_bed_ratio(ratio):
    if ratio > 0.5:
        return '2_preferred'
    elif ratio > 0.25:
        return '1_sufficient'
    else:
        return '0_insufficient'
```

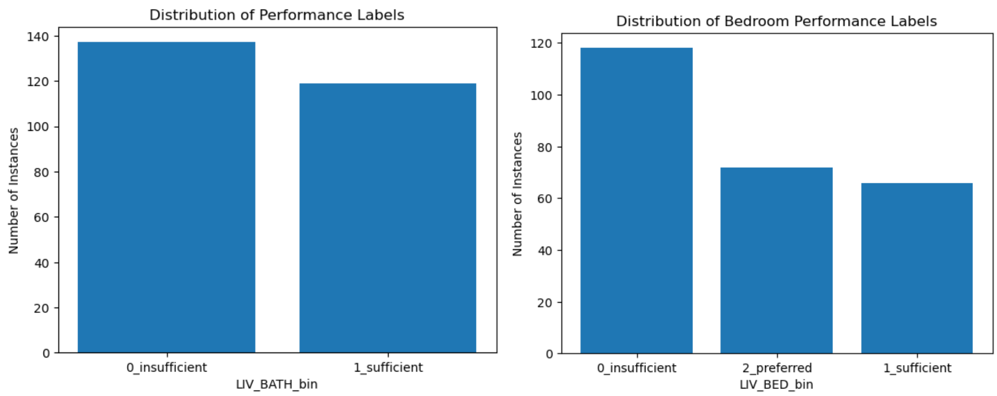


Figure 71: Class distribution of bedrooms and bathrooms.

6.1.2 Feature Pool

Ideally there is an exhaustive list of features available to us to select our feature list for further testing. This step is manually done based on the assessment of features during the exploratory data analysis phase.

Feature selection is a critical part for building a machine learning model where the most relevant variables from the dataset are identified to build a predictive model. The features have a direct influence on the model's performance; therefore, a selection procedure needs to be conducted and testing the most influential variables for the model's performance in terms of accurate prediction of the target variable.

The selection of feature is done by index values in the dataset. A dataframe was created in the form of tuples to show the index value per feature so that manual selection of the feature set can be done from the feature pool.

Below describes the selection of all possible features that is included for the feature subset selection.

```
# Create a DataFrame with column indices and names
index_names_df = pd.DataFrame({'Index': range(len(Swiss_Sim.columns)), 'Column Name':
Swiss_Sim.columns})

# Convert DataFrame to a list of tuples (index, column name)
index_names_list = list(index_names_df.to_records(index=False))

column_indices = [[5,7], # Building information to associate different dataframes with
                  [8,14,24,25,27], # Geometry-based features
                  [16], # Adjacencies and relationships
                  [297,298,299,300,301,302,302], # Centrality
                  [304,305,306,307,308,309,310], # Distance to entrance door
                  [311,312,313,314,315,316,317], # Betweenness
                  [318,319,320,321,322,323,324], # Closeness
```

```
                  [325,326,327,328,329,330,331], # (living?) Room distances
                  [332,333,334,335,336,337,338], # Living - Dining distance
                  [339,340,341,342,343,344,345], # Bathroom distance
                  [346,347,348,349,350,351,352], # Kitchen distance
                  [353,354,355,356,357,358,359], # Distance to balcony
                  [367,368]] # Layout biggest rectangle length and width
```

6.1.3 Multi-Output Evaluation Metrics

Because the model will have multiple output per visual sightline class, we also need to evaluate the overall model's performance in its ability to classify multiple outputs correctly. The way this is handled is by adding multi-output evaluation metrics to measure the overall performance of the model. The evaluation metrics are explained in the sub-section 5.1.6 Evaluation Metrics of Machine Learning Performance. In summary, the subset accuracy requires all labels to be correct whereas the hamming loss calculates the fraction of incorrect labels.

```
# Custom scoring function for subset accuracy
def subset_accuracy_score(y_true, y_pred):
    return np.mean(np.all(y_true == y_pred, axis=1))
subset_accuracy_scorer = make_scorer(subset_accuracy_score)

# Custom scoring function for Hamming loss
def hamming_loss_score(y_true, y_pred):
    return np.sum(y_true.values != y_pred) / np.size(y_true)
hamming_loss_scorer = make_scorer(hamming_loss_score, greater_is_better=False)
```

6.1.4 Sequential Feature Selector

Using the Random Forest classifier, we perform two wrapper-based filter selection method. First we perform a forward sequential feature selector borrowed from SKLearn library, then we perform backward sequential feature selector to compare the results for the most suitable feature subset selection. This method balances computational cost with usefulness. An exhaustive search of all possible sequence using all features get us the most suitable feature subset which can be performed at a later stage to validate the best feature subset.

Inside a loop, we perform the following actions:

Count the number of features where max_n_features takes the number of columns in the dataframe:

```
for n_features in range(1, max_n_features + 1):
```

Initialize the random forest classifier wrapped by SKLearn's *MultiOutputClassifier* module:

```
    multi_target_rf = RandomForestClassifier(n_estimators=n_estimator,
random_state=random_state)
```

Performing the sequential feature selector optimizing for higher subset accuracy using the 5 cross-fold validation:

```
sfs = SequentialFeatureSelector(
        multi_target_rf,
        n_features_to_select=n_features,
        direction='forward',
        scoring=subset_accuracy_scorer,  # Optimize for subset accuracy or hamming loss
        cv=cv, # k-fold = 5
        n_jobs=-1
    )
```

Fitting the feature selection on the training data and transform both training and test set:

```
    sfs.fit(X_train, y_train)
    X_train_selected = sfs.transform(X_train)
    X_test_selected = sfs.transform(X_test)
```

Re-initialize the random forest using the same random seed:

```
  multi_target_rf = RandomForestClassifier(random_state=random_state)
  multi_target_rf.fit(X_train_selected, y_train)
  y_test_pred = multi_target_rf.predict(X_test_selected)
```

Finally, evaluate the model's feature subset on both multi-output metrics:

```
  hamming_loss = hamming_loss_score(y_test, y_test_pred)
  subset_accuracy = subset_accuracy_score(y_test, y_test_pred)
```

In the code documentation, a backward selection was also performed to compare the two results:

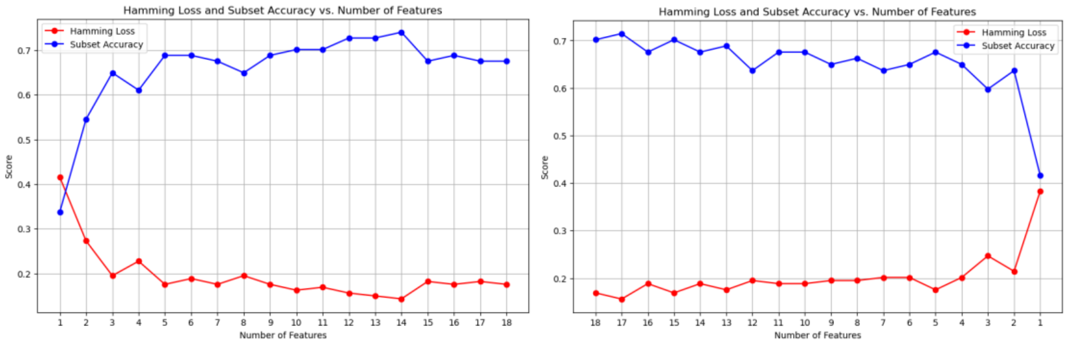


Figure 72: Results of the feature selection using the sequential method.

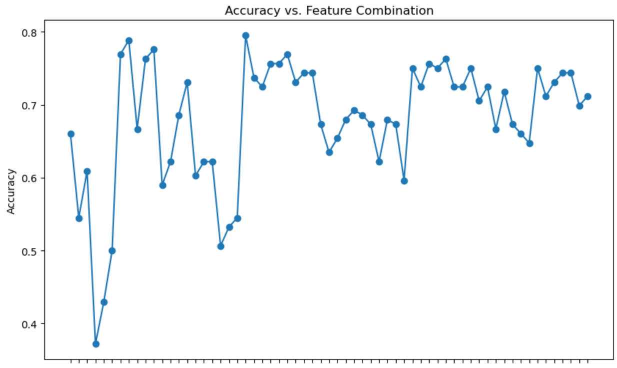


Figure 73: Results of the exhaustive feature selection method on a limited number of features using one classification output (living to kitchen sightlines).

6.1.5 Hyperparameter Tuning

A grid search is performed to improve the performance of the model ([SKLearn, RandomForestClassifier]). The grid search is computationally expensive but allows for testing all possible combination from a set of pre-defined hyperparameters whereas randomized grid randomly samples parameters.

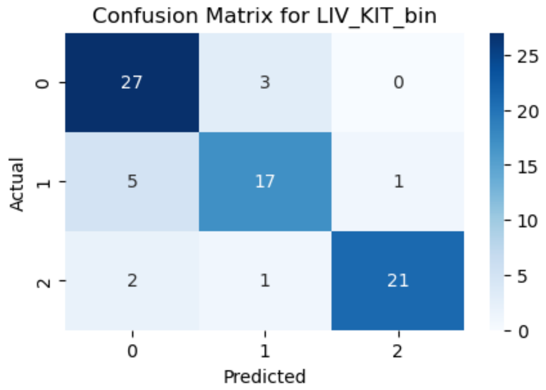
The parameter grid for the search is defined in the notebook:

```
# Define hyperparameters for grid search
param_grid = {
    'n_estimators': [int(x) for x in np.linspace(start=50, stop=500, num=25)],  # Number of trees in the forest
    'criterion': ['gini', 'entropy'],  # Function to measure the quality of a split
    'max_depth': [None, 10, 20, 30, 40, 50],  # Maximum depth of the tree
    'min_samples_split': [2, 5, 10],  # Minimum number of samples required to split an internal node
    'min_samples_leaf': [1, 2, 4],  # Minimum number of samples required to be at a leaf node
    'max_features': ['auto', 'sqrt', 'log2'],  # Number of features to consider when looking for the best split
    'bootstrap': [True, False]  # Whether bootstrap samples are used when building trees
    # 'max_leaf_nodes': [None, 10, 20, 30],  # Maximum number of leaf nodes
    # 'min_impurity_decrease': [0.0, 0.01, 0.1],  # Minimum impurity decrease to split a node
    # 'oob_score': [False, True],  # Whether to use out-of-bag samples to estimate the generalization accuracy
```

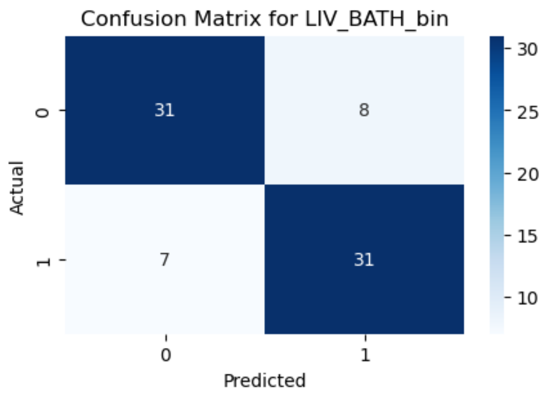
```
    # 'warm_start': [False, True],  # Reuse the solution of the previous call to fit and add more estimators to the
ensemble
    # 'n_jobs': [None, -1]  # Number of jobs to run in parallel
}
```

6.1.5 Evaluation

Finally, based on the results from the hyperparameter search, we take the model parameters and evaluate it using confusion matrix including the precision, recall, f1-score, and multi-output evaluation metrics defined earlier. We evaluate each output individually to give us a more detailed overview of the performance for each output, i.e. the sightlines from living to kitchen, living to bathroom, etc.




```
Accuracy for LIV_KIT_bin: 0.8441558441558441
Classification Report for LIV_KIT_bin:
                precision    recall  f1-score   support

0_insufficient       0.79      0.90      0.84        30
  1_sufficient       0.81      0.74      0.77        23
   2_preferred       0.95      0.88      0.91        24

      accuracy                           0.84        77
     macro avg       0.85      0.84      0.84        77
  weighted avg       0.85      0.84      0.84        77
```




```
Accuracy for LIV_BATH_bin: 0.8051948051948052
Classification Report for LIV_BATH_bin:
                precision    recall  f1-score   support

0_insufficient       0.82      0.79      0.81        39
  1_sufficient       0.79      0.82      0.81        38

      accuracy                           0.81        77
     macro avg       0.81      0.81      0.81        77
  weighted avg       0.81      0.81      0.81        77
```

```
Hamming Loss: 0.16883116883116883
Subset Accuracy: 0.7142857142857143
```

Figure 74: Confusion Matrix for each output visualized in the notebook.

6.2 Neural Network Model Setup

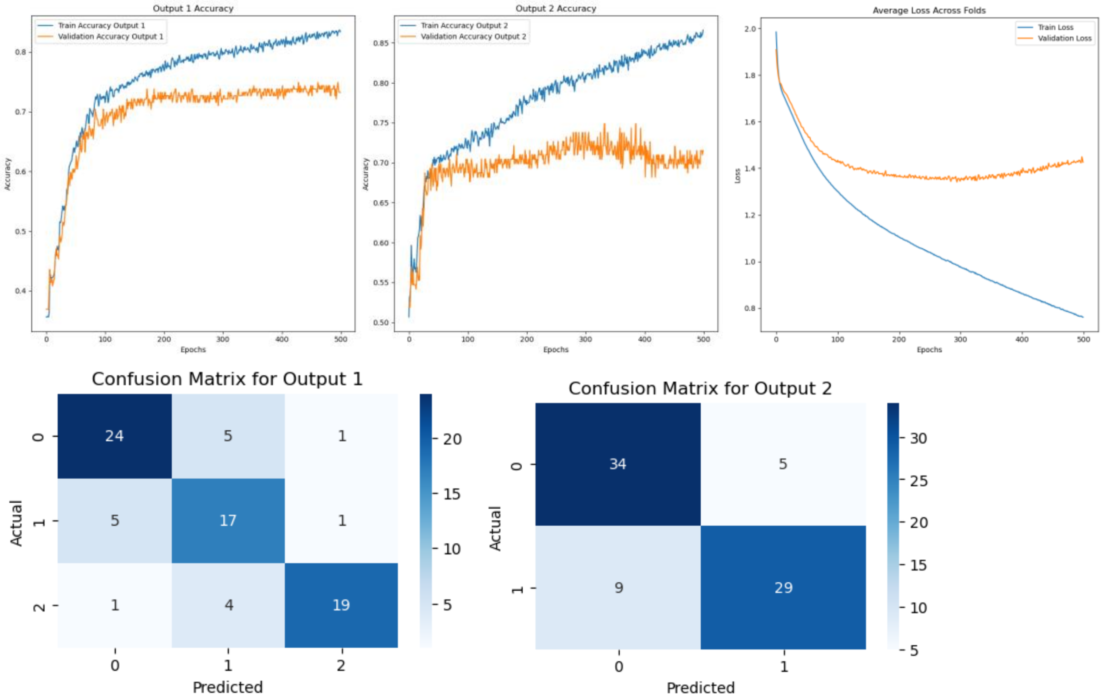
The setup of the neural network variation for the multi-output classification model follows the same setup as the one previously mentioned for the Random Forest Classifier. The change in this notebook is the hyperparameter grid used in a neural network, one-hot-encoding, which is to represent the classes in matrices, for compatibility with the tensor-based neural network from TensorFlow library (Novack, 2020).

We use SKLearn PreProcessing library for performing the OneHotEncoding (SKLearn, Encoding categorical features):

```
y1 = OneHotEncoder(sparse_output=False).fit_transform(y['LIV_KIT_bin'].values.reshape(-1, 1))
y2 = OneHotEncoder(sparse_output=False).fit_transform(y['LIV_BATH_bin'].values.reshape(-1, 1))

X_train, X_test, y1_train, y1_test, y2_train, y2_test = train_test_split(X, y1, y2, test_size=test_size,
random_state=random_state)

# Encode the target variables
```

```
label_encoder_1 = LabelEncoder()
label_encoder_2 = LabelEncoder()

y['LIV_KIT_bin'] = label_encoder_1.fit_transform(y['LIV_KIT_bin'])
y['LIV_BATH_bin'] = label_encoder_2.fit_transform(y['LIV_BATH_bin'])
```

A baseline reading was done by borrowing a model architecture from the literature (Ali et al., 2022) to get an initial indication on the training progress:




```
Accuracy for Output 1: 0.7792207792207793
Classification Report for Output 1:
              precision    recall  f1-score   support

           0       0.80      0.80      0.80        30
           1       0.65      0.74      0.69        23
           2       0.90      0.79      0.84        24

    accuracy                           0.78        77
   macro avg       0.79      0.78      0.78        77
weighted avg       0.79      0.78      0.78        77
```

```
Accuracy for Output 2: 0.8181818181818182
Classification Report for Output 2:
              precision    recall  f1-score   support

           0       0.79      0.87      0.83        39
           1       0.85      0.76      0.81        38

    accuracy                           0.82        77
   macro avg       0.82      0.82      0.82        77
weighted avg       0.82      0.82      0.82        77
```

```
Hamming Loss: 0.2012987012987013
Subset Accuracy: 0.6233766233766234
```

Figure 75: Baseline reading using a neural network for training the model on the entire feature set.

Considering the current model considers only 2 outputs / indicators, i.e. visual access between living to kitchen and bathrooms, hyperparameter tuning for the neural network remains an area for further development upon the completion a full assessment model.

6.3 Results

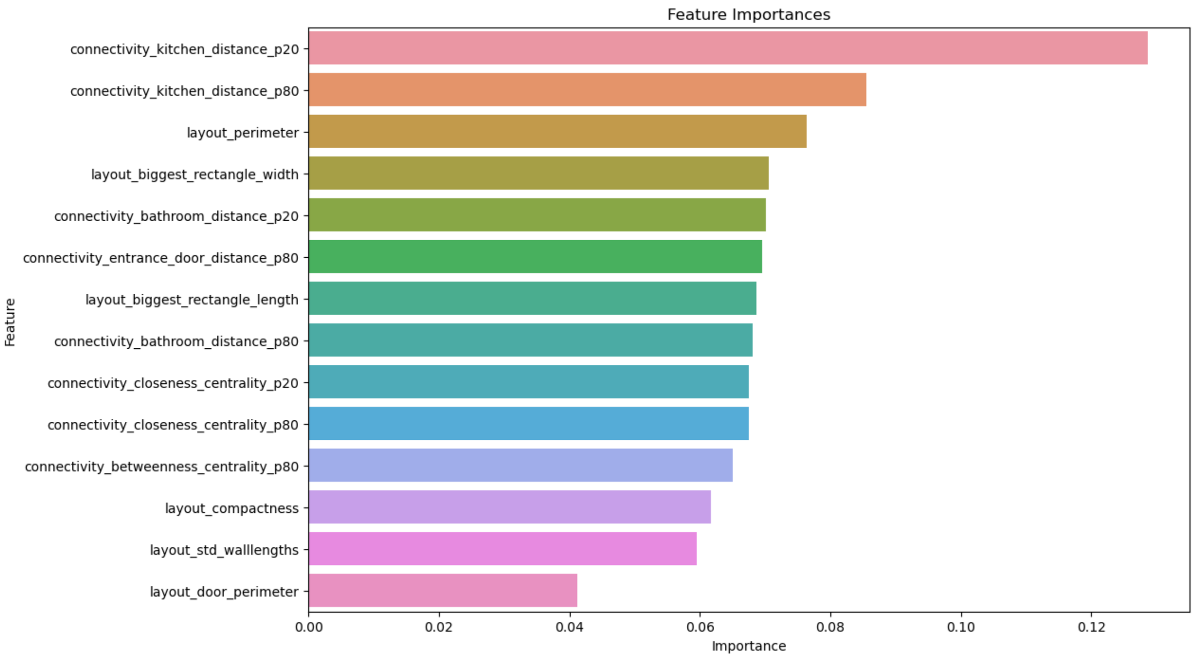
First looking at the Random Forest Classifier, we can see upon completing the model we have an overall subset accuracy of around 70% and hamming loss of 17%, meaning that 17% of the labels on average were incorrectly labelled. The feature selection arrived at a set of 14 features. On an individual output, the accuracy is over 80% but since we are interested in building a model that can generalize the quality of floor plans based on several assessment indicators, we should pay close attention to the subset accuracy and hamming loss as performance metrics of the model. Even though we have a relatively limited feature pool, the model is able to predict the visual access classes and there is enormous potential for expanding the data to include additional assessment indicators to support the early-stages of design that can provide generalized assessment on dementia-friendly design with respect to an entire floor layout. The neural network results is not yet fully tuned and suffers from overfitting concerns and generally does not generalize floor layouts as well as the Random Forest model. At this stage with such limited data, the neural network is setup for future expandability as the model increases in complexity which might necessitate deeper neural networks.

6.4 Discussion on the Results

6.4.1 Limitations of the Features

In this iteration of the model, the feature selection procedure was streamlined to use the wrap-based filter method to assign the feature subset that is most suited for the model. The feature pool, although currently is still a quite expansive list, still leaves a lot of room to be desired. Many of the features from the feature set had null or NaN values which had to be eliminated from the test. More features need to be added, including addressing the null-value features from the Swiss Dwellings. To name a few features to consider including in the pool: the indoor solid-to-wall ratios, number of doors separating living to other spaces, the angles of the walls, distances between walls, sequence of spaces, spatial hierarchy for overall spatial layout, zone shape complexity, and corridor moments of decisions.

The feature importance ranking, averaged across both target variables, reveals that the distance-based features are the most effective for determining the class. While designing kitchens to be central is not a new discovery, it does show that the model does indeed benefit from having kitchens closely positioned to the living room. The time constraints of this thesis project did not allow further investigation of additional features and test it against a complete assessment model, which warrants further investigation on the usefulness of a machine learning model trained on wayfinding quality indicators for generalizing floor plan quality with respect to the early-stage soft design criteria.



The feature extraction data from Grasshopper, which was an attempt to expand on the current feature pool, was not included in this model test due to its limited ability to make accurate predictions. This can be a good place to start to define a script within Grasshopper to expand the feature set and combine them with the Swiss Dwellings features.

Feature selection could be more thorough and less dependent what's currently available. The features in this exercise have been manually selected based on their plots and histograms, and ultimately added all the features and used a more computationally-efficient way to select a feature subset, i.e. using the wrap-based filter method for sequential feature selection. No mathematical transformation has been applied and can be considered, for example, logarithmic or square root transformations to better control the outliers in the feature set.

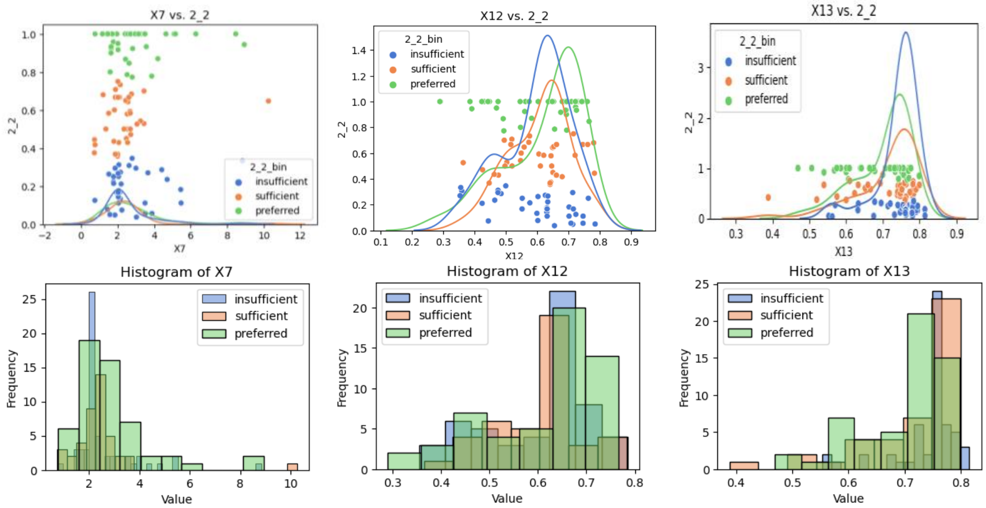


Figure 76: a closer look again at the pair plots and histograms for the Grasshopper features that were selected in the testing.

<u>6.4.2 Future Expandability with Neural Networks</u>

More work still needs to be done to improve the reliability of the model on unseen-before data. The assessment indicators for wayfinding quality are many and will ultimately contain different spatial experiences that will necessitate additional spatial features to improve the prediction of multiple multiclass outputs in one model. As the complexity of the assessment grows, it might also be useful to incorporate more complex data such as visibility graph analysis measures to better describe the spatial features on a floor plan level, and potentially future users of this model will get assessment results based on their visibility graph analysis results. While neural networks offer greater expandability for handling complex feature sets and multiple assessment indicators, the interpretability of random forests and simple architecture can be valuable for understanding the model's decision-making process and identifying key features influencing wayfinding quality throughout the development process for the wayfinding quality assessment model. Ultimately, using a neural network architecture has to be paired with a complex enough prediction task which this project could increase to that level with the introduction of additional assessment indicators and features.

7 Deployment in Architectural Design

7.1 AI-Enabled Design Process

7.1.1 Current Application of AI in the Practice

Machine learning tools in architecture primarily fall in two categories (Rafsanjani & Nabizadeh, 2023):

1. Surrogate modelling process for replacing time-consuming modelling process with a predictive model that can properly detect patterns from historical data to make generalized quick decisions.
2. Design-assisting modelling that is integrated into the intuition of designs for better facilitation of architectural process responding to design task without analytical explanation.

Applications of AI in architectural design covers a wide range of potential benefits for the design process. In particular AI provides great advantage in early design stage for providing insights on daylight, wind, and structural analysis. Autodesk Forma demonstrates one example where AI supports the decision-making process during the schematic design phase (AEC Plus Tech, 2023). The problem Autodesk is attempting to solve using AI is "*give Architects all the relevant insight when they start a design project; augment their design exploration capabilities; and inform the design process with relevant analysis*" signaling towards the new direction AI will find in the design industry as a companion for providing analytics on schematic designs. This approach aligns with the surrogate modelling process in machine learning.

Despite the advantages of AI, it is still not universally adopted. RIBA's review on the subject of AI applications in the practice showed 41% of practitioners have at least occasionally used AI in their project, but only 2 percent use AI for every project (RIBA Artificial Intelligence Report 2024). The reports cites survey results showing that the majority of practitioners uses AI for early design stage visualization (i.e. Dalle and Midjourney text-to-image generator) followed by generative and parametric design model generation. Furthermore, there is an overarching sentiment across the entire results in the report that AI is a potential risk to the industry, and concludes on a note that transparent communication between industry experts in the AI development field and architectural professionals to help clarify the misconceptions about AI and to foster trust in AI technologies.

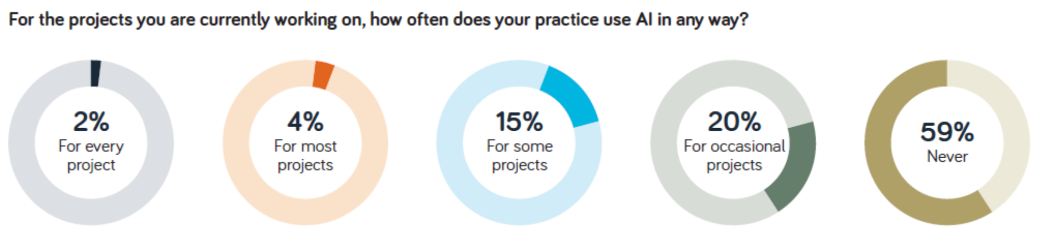


Figure 77: RIBA's survey response in 2024 related to AI applications in the practice.

7.1.2 Notable Practitioners that Use AI in the Design Process

Zaha Hadid Architects are known for their use of text-to-image generator, an AI model developed by Midjourney a generative AI company based in San Francisco, where they it is used for design ideas for new projects, prompting the AI to imagine designs in the style of Zaha Hadid (Barker, 2023). As observed in the literature study, Foster & Partners are publishing papers on innovative ways to use machine learning to support the design decisions in the early stages to inform spatial and visual connectivity of office layouts. In 2019, Gensler explored machine learning applications utilizing natural language processing techniques to analyze large amounts of survey comments and clustering them based on their similarity which provided insights into user preferences and spatial experiences which allows their designers to make informed decisions on FF&E specification and balancing it with cost (Gensler Research Institute 2019).

7.2 Design Case Scenario

The wayfinding assessment tool would fall under the analytical AI-enabled assessment tools that provides additional insights to the designer to base their decision-making process. The tool can be used in the evaluation of design alternatives for a new design proposal for residential care spaces intended for users living with dementia. The architect would have a brief of requirements for instance, to ensure that the new living facility follows the current-best practices established in the DDP manual with large emphasis on promoting wayfinding quality to improve the resident's sense of autonomy and independence.

The AI tool will bridge the gap between the missing expert validation in the early design stages as it is often not the case dementia care experts with a design background are involved in the design process either due to lack of experts in the field or cost associated with having expert validations as part of an integrated design team early on.

To bridge the expertise gap and augment design with analytical insights, the architect will have to install the model on their computer so that they can use it to evaluate multiple design options and gets feedback on the wayfinding quality in an iterative process between a designer conceptualizing new layouts and the AI giving feedback.

One approach to integrate an AI assessment tool in the conceptualizing step is to conduct a design charrette with the entire design team, sketch layouts based that satisfies the design brief / program of requirements, upload the sketches to a program to convert the sketches into features that the model can understand, then feed them into the predictive model to get feedback on the layout. The model will give back results on the wayfinding quality based on its training which the designer will use as an additional input for shaping the next iteration of design concept, repeating the process until the design options are locked in for further detailed studies. Once completing this process, selected options have already been verified to have good wayfinding quality.

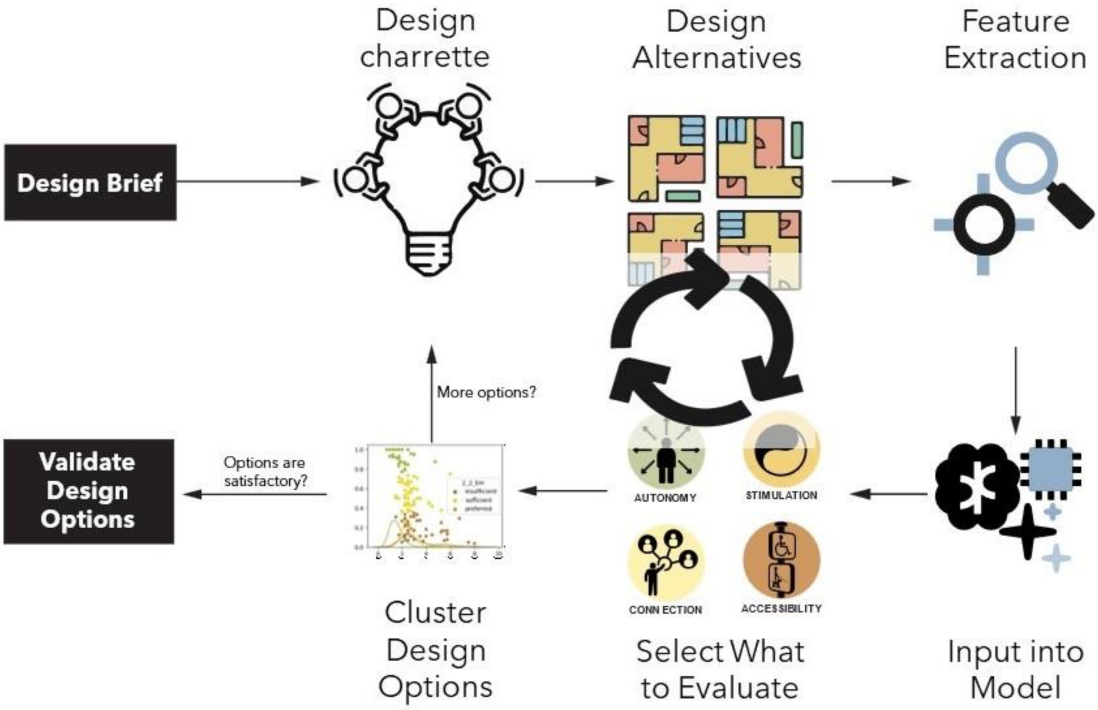


Figure 78: AI as the link in an iterative design step taking concept sketches by designer, converting the file to a format suitable for the model, receive feedback, then proceeding to detailed design after designer is satisfied with their design options.

Thereby allowing the designer to dedicate their efforts into complying with the design brief while simultaneously getting feedback by the model on the human side of design early on in project's lifetime.

<u>7.2.1 Testing Alternative Design Options</u>

In this hypothetical scenario, 6 design options have been supplied from the Swiss Dwelling dataset that the model has not been trained on.

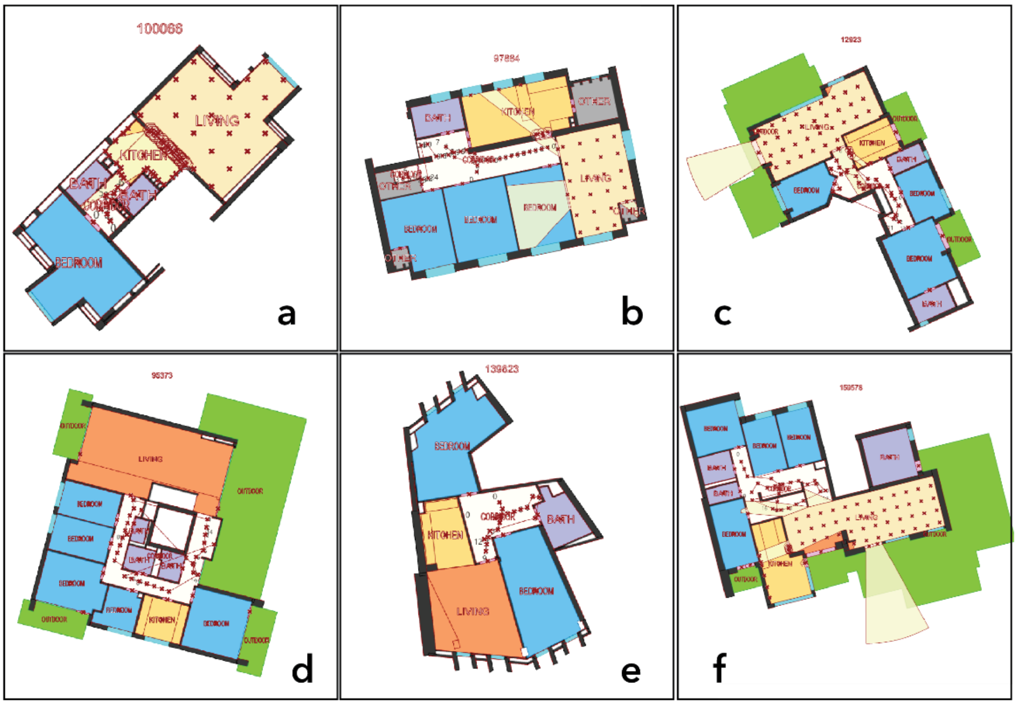


Figure 79: hypothetical design alternatives for evaluation and approval by client.

The 6 samples are presented here as potential design options for a single-story dwelling that will house a family including a person with pre-stages of dementia. In this hypothetical scenario, the 6 floor layouts are design options that were picked by the designer working with the architect based on their budget constraints, layout preferences, and different living room sizes.

The design options are then prepared to be evaluated by the model on the soft criteria it is trained on, specifically if the household promote a sense of autonomy for an individual living with dementia based on the DDP criteria the model was trained on.

The different floor layouts are converted into numeric features for the model to assess, and the architect receives feedback on the performance design options giving them insights on the soft, qualitative side of their floor options to present to their client.

```
1/1 ━━━━━━━━━━━━━━━━━━━━ 0s 86ms/step
     unit_id    area_id predicted_performance      actual assessment
100   159578  1665137.0            sufficient      sufficient (37%)
127   139823  1461812.0             preferred      preferred (100%)
129    95373   941667.0          insufficient      insufficient (0%)
130    12923   914963.0          insufficient      insufficient (19%)
131    97884   965601.0          insufficient      sufficient (57%)
132   100066   986826.0             preferred      Preferred (100%)
```

Figure 80: results from a preliminary test set to check the accuracy of the model trained on 205 floor using 4 features and 1 assessment indicator.

The architect now also has specific recommendations to which floor layouts might have better likelihood to allow their client to live independently as their condition progresses over time.

7.3 Potential of AI-Driven Architectural Design in Dementia Care

At this stage, the model is only trained on two criteria from the EAT checklist. The potential to expand to multiple criteria and assess wayfinding quality, and encompass all aspects of early-stage soft design criteria, based on multiple criteria has potential to improve the possibility for a model that can provide more useful prediction on the wayfinding quality of an entire floor plan. The most immediate and useful way to improve the usefulness of the model is to add all other criteria that are assessed from the living room, such as sightlines to dining, sightlines to corridor, and so on. On a complete (soft) design criteria level, the model has the potential to generalize the results of entire floor plans based on the categorical designation of the design criteria. I.e., the floor plan promotes a sense of autonomy, fosters sense of connection, sound stimuli aids wayfinding, and toilets are accessible.

7.3.1 Sketch Option Validator

During integrated design charrette, the medium of choice for communicating design options is quickly through sketches with the all the project stakeholders. In this rapid design session, time is of the essence. The potential of a soft-criteria analytical model will serve as a guide for the entire team on pre-defined scope for objectives of the project, i.e. to support personal autonomy and social integration. The usefulness of a model trained to recognize the soft values in floor layouts can be deployed in the brainstorming sessions to provide data-driven assessment on the quality of different design options to allow the team to make informed decision in a timely manner.

The compatibility of a machine learning model in analogue sketches can provide challenges. However, this can also be solved using AI. There are existing computer vision models that can translate floor plan drawings into vectorized data (Pizarro, 2022) which in turn be used to extract their features to feed into the wayfinding assessment model. Computer vision models specifically to recognize sketches is an area of research that can soon become a viable option for converting analogue (or digital sketching using stylus), for example a sketch-based system called a.SCatch developed by researchers that can differentiate between different line weights which allows architects to search for new floor plans by sketching parts of it (Ahmed et al., 2014). Developing a computer vision model for the purpose of floor layout recognition and feature extraction is technically feasible using image-based convolutional neural network that takes images as inputs and outputs the necessary features the model is trained on.

7.3.2 Multi-Objective Optimization

Another instance where such a model can be valuable during complex projects that tackles multiple engineering objectives in the early stages. For instance, a project that needs to perform structural optimization for earthquake resilience or high-rise wind loads that balances various objectives affected by structural design configuration response to seismic loads such as shear wall torsion, flexural shear, and drift (e.g. of a multi-objective optimization where shear wall positioning impact visual access Zhang & Meuller, 2017). Shear walls placement along the floor plan will have a direct effect on visual access between spaces, a critical aspect for dementia-friendly design that needs to be carefully managed in the early stages. An additional optimization criteria to structural design can include dementia-friendly design criteria for residential care communities in earthquake-prone regions such as Türkiye. An engineer can then balance the structural design requirement for structural integrity while maintaining acceptable spatial layout that supports ease of wayfinding by virtue of visual access continuity.

7.4 Roadmap for Distributing AI-Enabled Packages

7.4.1 Comprehensive Assessment Model

The roadmap for a general-purpose dementia-friendly assessment model starts by expanding on the assessment data to encompass all aspects of the floor layout that affect wayfinding quality and the 4 soft design criteria (see Appendix 2, Appendix 3, Fleming & Bennett, 2017). The method for which we measure the extent of floor layout compliance to the dementia environmental design guidelines is one of the first steps to tackle towards a more comprehensive model.

7.4.2 Expansion of Training Data

On the data front, participation from architects is essential for developing high-quality database of floor plans that have high diversity and quality from around the world that is dedicated solely for machine learning exercises. This participation from practice is essential as dataset collection for dementia facilities can be processed by building technologist into the correct format for the compatibility with the machine learning algorithms. Such initiative requires coordination between multiple entities, but it starts with architects and developers giving access to their floor plans on projects such as nursing homes, dementia care facilities, residential care units and so on for data scientists to compile into a dataset comparable to the Swiss Dwellings.

7.4.3 Launching an AI Project for Dementia-Friendly Architecture

Once the pre-requisite assessment models are established, and a robust geometry dataset is prepared, an open call can be organized to allow students, engineers, and scientists to explore machine learning models based on the building geometry and their assessment results. Open sourcing this collaboration to the general public allows for better integration with industry and academia. This phase won't be possible without having a complete assessment model that represent the most relevant early-stage design criteria architects need to be addressed in the early stages, and a high-quality dataset of floor plan geometries, but in the event those are available, this can allow for public participants to innovate software packages to serve the design practice to bridging the gap between early-stage assessment and final design validation of building designs with respect to dementia-friendly architecture. This also opens up multiple avenues for software development efforts such as plug-in packages that can be integrated in the toolbox of architects such as Revit.

Scientists and practitioners working in the construction industry can work together to diversify the publicly available datasets of floor plan geometry to accelerate the development of more human-oriented AI tools. Moreover, human-oriented AI tools need participation by multidisciplinary teams to evaluate the validity of the model and give feedback on best evidence available to base off wellbeing indicator for a select user group. Lastly, participations by the end user group, architects, and spatial designers, can support the development by testing the tools and providing feedback on the ways they prefer to interact with the model.

7.5 Conclusion

The roadmap to a human-centric AI analytic tool for the built environment requires further research. Software companies are already developing surrogate models to provide architects with insights into their design options without the need for time-consuming and costly studies. This allows architects to explore designs that have a high likelihood of performing well. Based on the results observed in the test set for the wayfinding quality model's performance, we conclude that this AI tool has the potential to become an important element in the design process for dementia care spaces. It could serve as an expert in dementia design principles, supporting designers in assessing soft design criteria that are difficult to measure during the design development phases.

8 Conclusion

The research presented in this thesis aimed to investigate an approach for measuring soft design criteria for assisted living building typology to develop a computational method for measuring them using machine learning. The soft criteria that had great impact on wellbeing was ease of wayfinding which was primarily measured through visual access. The wayfinding quality was defined as numeric values which was then used in the training of the AI model to predict the wayfinding quality based on a selection building features.

8.1 Answers to Research Sub-Questions

8.1.1 What are the essential qualitative spatial design features that promote wellbeing for people living with dementia?

There were several design principles that promote overall wellbeing for people living with dementia. Visual access has direct influence on the navigability of indoor environments which also influences perceived sense of community and promoting autonomy by virtue of intelligible layouts that does not cause confusion or a person to be lost in their environment. Wayfinding was also discovered to improve with additional stimuli such as sound and smell that reinforce the directionality of space for the person navigating their indoor environments.

8.1.2 How can we implement digital tools for assessing floor plan geometry with respect to ease of wayfinding based on dementia design principles?

The development of wayfinding quality indicator on Grasshopper proved to be a successful choice due to its user-friendly interface and adaptability to all types of data, such as importing floor plan datasets from '.csv' files as well as exporting data back to the dataset. The decision to add an additional outcome to the assessment score of 'preferred' to the EAT checklist for whether visual sightlines are sufficient or not, yielded diverse results on the sample floor plan dataset allowing the opportunity to experiment with machine learning model on a limited-size dataset.

8.1.3 What are the prerequisite data needed to build a machine learning model that predicts the wayfinding quality from floor plan design representation?

The primary prerequisite for building a machine learning model is a labelled dataset. To build a machine learning model that gives feedback on the wayfinding quality requires a rigorous process of extracting features and methodically testing them to discover the most suitable features to allow for greater prediction accuracy. The labelled dataset in itself is important, but the feature selection process is the most important step that influence the outcome of the model's performance. A list of features for predicting wayfinding quality indicators were highlighted in this research which include distance-based features and geometric properties of layouts. Right now we answered this question using the feature pool available during the project's timeline, but a closer examination on what spatial features are the most meaningful for visual access needs additional attention.

8.1.4 To what extent can a machine learning model predict wayfinding quality from floor plan information?

The machine learning model was having a moderately successful attempt at predicting the wayfinding quality of floor plan geometry based on visual sightline data using both random forest and neural network architecture which suggests there is room to improve, possibly by expanding the dataset and improving the model by trying a less complex model architecture for assessing a single performance indicator-building method for feature selection for multiple assessment indicators. The model performance baseline reading shows a consistent 70-80% accuracy which already signals that the methodology works although it is currently limited by the size of feature pool available for the machine learning task. Through the feature combination selection and hyperparameter tuning, it was able to improve the model's accuracy, and therefore, a machine learning model can provide good approximation of wayfinding quality based on floor plan information although dedicating more time on feature extraction and selection can significantly improve the model's applicability.

8.1.5 In what way can the AI model be deployed in the design process?

Analytical models such as the wayfinding quality assessment tool can be a validation tool for design alternatives during the early stages of a design project. The wayfinding quality assessment tool serves as a companion to the existing architect workflow to bridge the gap between lack of expertise in the area of dementia design care spaces and building design practitioners.

8.2 Answer to Main Research Question

- How can artificial intelligence support the design of dementia-friendly architecture?

AI can support the design of dementia-friendly architecture by first measuring qualitative assessment of dementia design principles into numeric values that can be interpreted by a computer. This process involve expert opinion from various disciplines such as computer science, architects, dementia care specialists, environmental psychologists, and subject-matter experts depending on the DDP. But in simple terms, the assessment of qualitative criteria for dementia design principles is the first step towards developing an assessment algorithm to assemble the required dataset for building the AI model. The path to creating a model with high accuracy is iterative and requires end-to-end manipulation of data from the very beginning of the digital pipeline all the way to the end. The AI model can then be used to support the design of dementia-friendly architecture by giving feedback on the soft criteria quality to compare different design options, effectively forgoing the assessment procedure of a complex and multivariable problem in the early stages of design, affording architects the time to iterate more effectively between different concept design alternatives, and bridges the gap between DDP expertise and early stage design development.

8.3 Discussion on Machine Learning Framework

Feature selection is one of the most critical steps in the entire machine learning process that has been demonstrated in this thesis. The feature pool was introduced from the Swiss Dwellings simulation dataset. Active involvement in feature extraction through Grasshopper facilitated a deeper understanding of the model's internal workings, despite the limited success of the Grasshopper-derived feature set.

The machine learning framework for feature nomination from feature pools to feature sub-set provides a good first step to methodically introduce new features and assessment indicators one by one to building the model. The current framework for selection features had moderately successful results. The need to expand the training set is a priority, and also the feature pool with an extended exploratory data analysis step before proceeding to the model-building phase.

The Grasshopper assessment algorithm for floor layout using visual access to determine wayfinding quality allowed for greater control to dictate what data to generate and storing them in neat files for later retrieval. Grasshopper environment provides a good platform for experimenting with many options; however, it might be worth investigating to extract the features of floor plans results using depthMapX from Space Syntax Laboratory to use the numeric values from the visibility graph analysis as the basis for the assessment of wayfinding quality. What is interesting is that depthMapX is an open-source software with the entire code available on GitHub, making it more affordable and accessible by the practitioners compared to Grasshopper's cost barrier to entry. What Grasshopper excelled in was being able to import data and manipulate the data easily directly from the Swiss Dwellings dataset. Using a program dedicated to advanced analysis on spatial and visual connectivity might give better performance indicators to assess wayfinding quality for dementia-inclusive design. For the limited size of dataset available in this thesis, Grasshopper was sufficient, and the assessment algorithm was an asset to continuously re-iterate the algorithm's code until it was able to assess every single floor layout regardless of its complexity or orientation.

8.4 Conclusion

An AI-enabled assessment tool for wayfinding quality of indoor environments was demonstrated to be a viable direction for building AI models that give feedback based on numeric values derived from visual perception analysis measured using the isovist method. The final model was able to give prediction based on two assessment indicators based on sightlines from living to kitchen and bathrooms with an accuracy of around 80% for both outputs on the test set using both random forest classifier and a neural network. The test set shows promise for classifying wayfinding quality based on visual sightline data, although currently limited to assessing layouts from the Swiss dwellings.

8.5 Limitations and Challenges

8.5.1 Limited Dataset

Despite my best efforts to have diversity of floor plans by manually removing duplicates or units that are too similar, it might be still too homogenous, and the dataset could have benefited from a more diverse set of geometries that has different living room sizes and more varied spatial organization of rooms. Especially considering that the larger the living room size is, the more test points there are, and more data to assess wayfinding quality. The exploratory data analysis charts show most living room sizes are around the same range despite the differences in the number of bedrooms per dwelling, which ideally should change depending on the number occupant per dwelling.

Figure 81: a scatter plot showing the living room area compared to the number of bedrooms available in a single-story dwelling.

The Swiss Dwellings dataset provided a solid testing ground to build with a machine learning model for wayfinding quality assessment. Its biggest limitation is that it does not accurately represent dementia care facility indoor environments, although its limitation could be overlooked because it does contain the spaces needed to conduct preliminary studies (i.e. kitchen and living area which here also found in dementia care facilities). Expanding to multi-story dwellings and exploring new sub-typologies within the Dwellings dataset might provide much needed expansion to the size of the training set. However, it is still necessary to approximate the dementia care environments, all the good and the bad examples from around the world, to serve as a more accurate training set for wayfinding quality within dementia care spaces.

8.5.2 Limited Predictive Ability of the Grasshopper Features

The process for improving the accuracy of the model proved to be challenging to discern strong relationships in wayfinding quality which could be due to the lack of variability in the floor layouts. All thirteen Grasshopper building geometry features did not show strong correlation with the target variable which indicate there might be two approaches to address this challenge. First idea is to either introduce building typologies that are different from the Swiss Dwellings, such as commercial or nursing homes, in order to get clear differentiation between the features and the target variable, or create synthetic floor plan geometry to help create less homogenous dataset. The second idea is to experiment with new feature sets that are not necessarily architectural descriptions of geometry, such as mathematical expressions of the geometry beyond mean values and area ratios.

The discrepancy in the distance measure was an insightful discovery indicating the sensitivity of the features. Both Grasshopper feature set and the Swiss Dwellings feature set has a distance measure for mean distance between living room to kitchen. The feature from Grasshopper had a grid of points where each point measured linear distance to the centroid of kitchen. This does not match with the way the Swiss Dwelling perform their measurement. Based on inspecting some of the geometry, it appears the distance measures are to the kitchen door instead of the centroid. A small detail like this made the feature measured in Grasshopper unhelpful for the prediction ability of the model.

8.5.3 Limited Assessment Indicator

The scope of this thesis is achieved to complete the entire process for one assessment indicator. In the end, 2 assessment indicators were introduced to the model. This is a major limitation that this current study has which can be overcome by expanding the assessment indicators and feature set. Although having more assessment indicators will give us more data to work with and make better conclusion, testing the model on just two assessment indicator as outputs proved to be valuable as it laid the foundation for the model building method for subsequent data expansion either more training data, more assessment results, or more features. One or two assessment indicator is not enough to generalize wayfinding quality from the living space, and therefore, next subsequent iteration should focus only on expanding indicators for this one room function to be able to better describe wayfinding quality for an entire room function.

8.5.4 Lack of User Testing

The model for measuring wayfinding quality has not been validated through user testing in dementia care spaces and residences. This limits the understanding of how well such a model is aligned with the actual wayfinding experience of people living with dementia. Although on a dementia assessment criteria level it meets the criteria for visual sightline, there is still more room for improving the effectiveness of more precise measurement of spatial experience and its influence on wayfinding ability.

8.5.5 Limited Assessment Metrics on the Test Set

The test set is understood as a whole how it performs using a confusion matrix and the evaluation metrics established in the thesis based on best-practices for model evaluation, class-based accuracy using precision, F1 score, and recall, and multi-output accuracy using hamming loss and subset accuracy. As the prediction task increases in complexity with more inputs and outputs, it will likely be a challenge to interpret the model's strengths and weaknesses using only these benchmarks at a high level. Additionally, examining the types of errors the model makes (i.e., false positives, false negatives) and identifying patterns or commonalities among misclassified samples by viewing the floor plans side by side can be an advantage. To make this process more manageable and streamlined, future improvements on this topic could consider a report template to summarize the main points observed whenever the model expands to provide more transparent progress over the model's performance and have a track record of different test result benchmarks to compare the impact of changes on the data with different attained benchmarks for every model iteration.

8.6 Recommendations for Future Development

8.6.1 Expanding the Dataset

The model will benefit from expanding the training set to include a wider variety of geometries, such as additional dwellings from different datasets or multi-story dwellings within the Swiss dataset. Including geometries related to commercial and office typologies found in Swiss dwellings might also be beneficial, as it would add more variety to the training set.

Furthermore, the field of AI would benefit from research focused on developing a methodology for generating synthetic floor plan geometries specifically for machine learning training. For dementia care, a collection of dementia care floor plans from around the world would be particularly valuable.

And finally, expanding the assessment criteria and the feature pool alongside an exploratory data analysis assessment on the feature with respect to every class label from each assessment criterion.

8.6.2 Multisensory Wayfinding

The current model focuses on visual access. Future research should investigate the integration of additional sensory modalities, such as auditory and olfactory cues. This will lead to a more comprehensive assessment of wayfinding quality as it would take into account the full sensory range an individual with dementia uses while navigating their indoor environments.

8.6.3 Incorporating 3D Model Information

The current assessment environment is in 2D space which loses out on the complexity of spatial quality. Future studies on wayfinding quality should also investigate 3D model space that will give more realistic assessment of wayfinding quality taking into account furniture and eye-level field of view.

8.6.4 Long-Term Effects of Layout on Individual Health

Studying the impact of floor layouts on the individual health level over long periods of time might help us learn additional insights on how layout influences quality of life for people living with dementia which could involve tracking the wayfinding abilities of individuals over time while tracking their condition as it progresses.

8.6.5 User Testing and Validation

The integration of VR experiences or field experiments might allow researchers to test various design features' influence on wayfinding in a controlled environment. This could lead to a more accurate assessment of wayfinding quality as it would allow the model to take into account the full visual experience of space. In summary, the relationship between visual access and ease of wayfinding should be tested more rigorously in experimental settings to deepen our understanding on the connection between visual access to wayfinding.

9 Reflection

The goal of this thesis was to respond to the question of what are the immeasurable side of spatial design that promotes happiness and wellbeing, how to measure it, and how AI can be deployed to help with this process. The conclusion was developing a methodology for arriving to user-specific design criteria that promote wellbeing, a measuring methodology as performance indicators for fulfillment of defined soft criteria, and a machine learning methodology to develop a model that can estimate the wayfinding quality of indoor environments. The resulting model was built on a dataset containing more than 250 floor plans as training data, the model (hyperparameter) tuning procedure of the model was done by experimenting with various model architectures and feature selection in order to attempt to improve the performance of the predictive abilities of the model.

Being exposed to a vibrant scientific community at the Faculty of Architecture and the Built Environment who are exploring wide variety of AI-oriented topics inspired me to specifically ask the question of how AI can help in dementia care design and combine both my passions in the same thesis topic: designing for wellbeing and computational design. The big overarching question posed at the beginning stages of the thesis of what the immeasurable side of architecture is that contributes to occupant happiness and how to measure it, allowed for the freedom to explore problems and solutions that may not have been explored otherwise.

9.1 Graduation Process

9.1.1 How is it aligned with the field of Building Technology?

My graduation thesis involves the field of dementia-inclusive design and artificial intelligence, which I believe are both important themes for the Building Technology Graduation Studio. Combining the two fields of dementia care environmental design and artificial intelligence to develop an AI-enabled framework for assessing wayfinding quality of floor plans with respect to the dementia care design principles proved to be a fulfilling task with both fields being well-researched and documented domains. On one hand, the design principles for dementia-inclusive design is well-established in terms of assessing existing facilities to determine how it influences user behavior and wellbeing, however on the other hand, the implementation of these design principles in evidence-based design approaches is still broadly being developed (i.e. Quirke et al. 2021) which signaled to me an opportunity to investigate this gap through digital tools aligning well with the AE+T's Chair of Design Informatics mission to develop and disseminate knowledge and know-how for topics related to designing built environments with special attention to the "*overall performance of buildings and built environments involving both soft (human) and hard (physical) aspects*" (Design Informatics - TU Delft , 2024) in addition to alignment with the faculty-wide ongoing research theme on Digitalization and Artificial Intelligence (Digitalisation and Artificial Intelligence – TU Delft , 2024). Moreover, the thesis project aligns with AE+T's Chair of Indoor Environment's strategy for "*Assessment – indicators: Which parameters or indicators and assessment methods can be used to explain the effects or response? What type of information? How to assess?*" (Indoor Environments – TU Delft Website, 2024) which is an integral part of the Building Technology field.

9.1.2 Product, Process, Outcome

The end product of this thesis being AI-enabled soft criteria assessment tool developed through the process of data collection and conducted through the Building Technology Graduation Studio framework through literature review, computational design applications, and applying the research. The process gave insightful answers into both fields of dementia care and human-centered machine learning assessment tools. The Swiss Dwelling as a case study for training data allowed for the thesis to apply the methodology using high-quality information that would otherwise not be possible to reach to this level of completion. The

Dementia Design Principles EAT Checklist served as a solid grounding to build upon a measuring methodology that is backed by studies to promote indoor wayfinding, and ultimately wellbeing for the intended user. The link to practice through Tangram Architecture and the dissemination of knowledge through my exhibition contribution for *Immeasurably Important* (Muis, 2024) allows for greater integration between science and practice by involving the general audience to comment on the overall mission behind this thesis and contribute to the development of future AI-related applications affecting our built environment and the design industry as a whole. This connection to practice allowed me to also develop my soft skills as a future scientist in the built environment to engage the public with my ongoing research, and receive feedback through public discourse. I believe science should always be continuously tested for its societal relevance through public engagements, lectures, workshops, and publications not only for subject-matter experts, but also for general public audiences.

I have learned through my thesis topic how to formulate soft design criteria, and discovered that they are context and user-dependent processes. It is a mind-expanding exercise in terms of allowing me to develop a deeper understanding on the correlation between building design and perceived wellbeing, in this instance wellbeing of people living with dementia. Elderly care facilities provided a narrow scope with more constrained variables affecting overall wellbeing, and with the help of conversations with expert in the field of elderly care and universal design, I was able to better narrow down the soft criteria to its fundamental level while still not losing many of the nuance occupant-wellbeing indicators, but just enough to continue my research to develop measurable methodology for preliminary wayfinding quality assessment procedure.

We also got a glimpse into what makes spaces friendly for navigation by people with dementia. Implementing a random forest classifier to interpret the features was useful to understand how one feature correlate with the navigability of spaces especially because it the data analysis was not very distinct and was able to spot only weak trends in the class label 'preferred'. When faced with an overwhelming possibility of features, using the exhaustive search and sequential feature selector were a good decision to eliminate assumptions and only select feature combinations that work together which adds a deeper level of control and justification to the feature set combination and see how well they aligned with the qualitative assessment of the plots from the exploratory data analysis phase on an individual class level. To reduce the complexity of the model-building even further, guiding the hyperparameter search space with both wide randomized search and narrow grid search adds another layer of depth to guide the model-building process to at the very least eliminate options that don't work well and potentially discover model architectures that work very well for wayfinding quality assessment. To avoid overly-complex models at this early stages of model development, using random forest algorithm on the test set is something that should be considered as a means to simplify the finalization of the first model iteration.

9.1.3 The Transferability of This Project's Results

The methodology for determining the soft criteria for a specific group can be done to other user groups especially ones that are sensitive to environmental conditions to improve the universal design quality of our built environment. While it is true that improving wayfinding is especially important for people living with dementia and is recognized as a desired outcome based on the universal design recommendations, it ultimately benefits everyone navigating indoor environment. More intelligible spaces ultimately benefits everyone. This type of improvement in our built environment is also known as the "curb cut effect" referring to the phenomenon where universal designs or systems that were initially developed to benefit a specific vulnerable user group with particular needs end up having cascading benefits to society.

9.2 Scientific and Societal Contribution

9.2.1 Scientific Contribution

This thesis expands the current knowledge on machine learning-based approaches for early design stage analysis by selecting a performance indicator commonly used by professionals in the field of wayfinding, the isovist analysis, and relating it to wayfinding quality for dementia care spaces. Moreover, this research expands on the available isovist-based AI tools by exploring a novel assessment methodology for indoor-environment wayfinding quality for occupants living with dementia.

9.2.2 Societal Contribution

The possibility of improving the design process for new elderly care facilities has the potential for cascading benefits, especially considering the nature of digital tools that can be disseminated easily through open-source practices and collective contribution from the programming community. On a practical level, AI assessment tools for soft design criteria related to dementia care will bridge the gap between architects and expert validation in the most critical stages of design that determines the wayfinding quality of a layout, the early design stage. On a broader level, an AI assessment tool for wayfinding quality will improve the ability for people with dementia in the future to cope better in their own environments allowing them to enjoy a dignified high quality of living.

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Floor plan sourcing for production of illustration:
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Appendix

Appendix 1: Project Plan

Appendix 1: Project Plan (cont'd)

PROJECTPLAN

1. Project Content

'unmeasurably important': *the 'hard values' of the 'soft values'*

... raises the question of how to intelligently integrate new technologies such as AI into the development and design process, resulting in a better outcome in every respect. This approach takes into account all relevant aspects, particularly the difficult-to-measure, soft values such as happiness, social well-being, and health, which are crucial for long-term high-quality use and often have indirect economic value.

Architecture and urban planning are bound arts. In a world of increasing complexity, spatial designers are confronted with an ever-growing number of principles and stakeholders. Beyond the usual considerations of location and program, the major transitions have an increasing impact, spanning climate, ecology, energy, economy, mobility, and demography. Various spatial demands in the Netherlands necessitate the intensification of existing cities to conserve scarce land for other purposes. This presents new challenges, such as managing local stakeholders and creating new housing typologies that combine higher density with healthy and pleasant living. City intensification also demands a focus on green spaces and water features, along with the management of heat stress. In an intensified city, we should aim for 'gross national happiness'—a place where people can coexist pleasantly without a sense of discomfort. Many of these objectives are not found in traditional requirements specifications.

Simultaneously, we are undergoing a technological revolution, that of Artificial Intelligence. Various AI tools are already being tested and used in the built environment. Expectations are soaring, as it is seen as the Holy Grail that enables faster and better design. AI can be a valuable tool for addressing increasingly complex questions, but it relies on available data. Many of the 'soft' values mentioned earlier cannot yet be captured in data, thus potentially fading into the background, which could be detrimental to the livability of the built environment. Furthermore, we have not yet fully grasped the creative process, as a significant part of it takes place in the realm of the subconscious. This is the challenge.

With this project, we investigate how, through practical examples, we can leverage the advantages of new technologies on one hand while, on the other, raising the quality of life in the urban environment to a higher level with original solutions that are tailored to specific questions and locations.
In short, this project concerns architecture and urban planning in the era of AI.

2. Background

The questions surrounding the built environment are becoming increasingly complex by the day. A significant construction challenge must take place in an already crowded city, and the urgency is high—it must be executed quickly. Simultaneously, it is inevitable that major transitions find their place in the process and design: climate and energy, demographic changes, and participation, involving non-professionals in the development and design process. Moreover, we find ourselves (once again) in a crisis in the construction and design world. The economic climate is unfavorable. More is expected while resources are dwindling. A dangerous reflex can already be observed: the use of AI in design processes with the assumption that this leads to quicker and better results. This is a significant pitfall.

With the project 'unmeasurably important,' our aim is to explore the possibilities of AI and interpret them in relation to the 'softer' aspects of spatial design. These softer aspects can create a lot of value (both socially and economically) but are still challenging to quantify in hard data. Hence, there is a risk that a design translation via AI from the program's requirements will not lead to an optimal result: the optimal accommodation of human activities. Apart from the (im) possibility of quantifying soft values such as 'happiness,' 'well-being,' and 'healthy living,' the principle of creativity (lateral thinking based on not knowing) seems to be at odds with that of AI: the (intelligent) assembly of already known data.

The thematic question, therefore, is how to intelligently integrate new technologies into the process, resulting in a better outcome in every respect. We place this question at the center of a series of exhibitions (starting at the Stadsschouwburg Alkmaar) and illustrate it through the work of our bureau and other participating parties in the field of AI, including various leading knowledge institutions. These two perspectives come together in the AI analysis, using various experts, to compare built examples of Tangram with an AI alternative for the same locations and the same program. The differences provide material for discussion.

'AI will not replace architects..
Architects that use AI
will replace the ones that don't'

2

Appendix 1: Project Plan (cont'd)

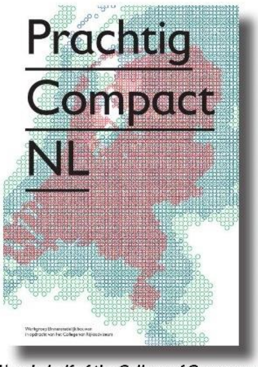
3. Personal motivation

TANGRAM, a renowned architectural and urban planning firm in the Netherlands, boasts extensive experience in designing projects across various scales and building categories. They are recognized for their commitment to achieving a harmonious balance between the functionality of structures and affordability. Their designs seamlessly integrate with specific geographic contexts while taking into account human-centric elements like psychology, human scale, social impact, historical context, nature inclusivity, and ecological considerations such as land use, green spaces, and water management.

TANGRAM's existence is rooted in their innate curiosity, notably following their success in Europan 1, where they explored the influence of changing lifestyles on the built environment. Their contributions extend beyond architectural work, encompassing education, research, and publications. They have collaborated with diverse disciplines to advance the field of spatial design and the future of spatial development, primarily in the Netherlands. Notable publications include 'Prachtig Compact NL' and 'Stad van de Toekomst, de meebewegende stad,' commissioned by government bodies and ministries in partnership with major cities and institutions. Their impact is also evident in opinion pieces and exhibitions, such as 'MÀ-SSA' and 'Balans: Dimensions of Sustainability,' which explores factors necessary for sustainable living environments.

Despite the seemingly disparate nature of these activities from their core architectural work, TANGRAM's influence and reach are substantial. Their overarching mission centers on raising awareness and fostering discussion of pressing issues that affect various stakeholders, including professionals, developers, policymakers, and end-users. Their current initiative aims to responsibly introduce the next technological innovation into the design process, particularly amidst housing shortages and complex societal transitions.

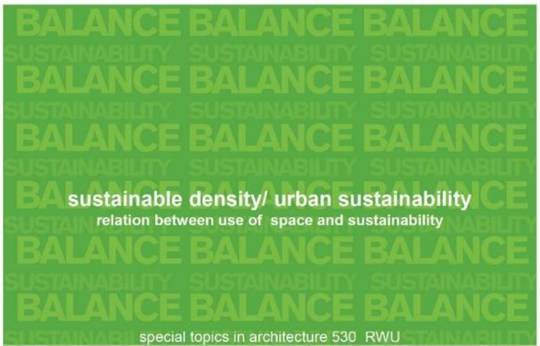
'Stad van de Toekomst' On behalf of the Ministries of Infrastructure and For-



'Beautiful Compact NL' on behalf of the College of Government Advisors (2010.)

'MASSA' exhibition at ABC Haarlem, meaningful emptiness (2003.)

Europan I 'Nomads Exist at a Higher Level" (1991. - Winning entry)

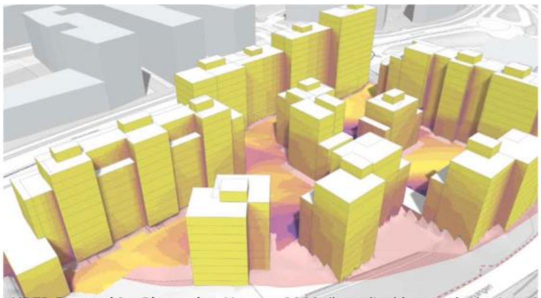


Balance' exhibition, dimensions of sustainability, including Haarlem, Almere, Almelo, Tilburg, Bristol (UK), Washington D.C. (USA) (2010-2013)

Appendix 1: Project Plan (cont'd)

4. Positioning

In the contemporary realm of design and development, a critical deficiency exists in considering the dynamic interplay between soft and hard values. There is a growing dominance of easily quantifiable factors, like economics and time, in shaping the criteria for new projects. This shift is reflected in the declining role and recognition of spatial designers, which includes architects, urban planners, and cityscape designers. Their potential to create value, both societally and economically, for the built environment extends beyond rigid programmatic requirements. This encompasses not only meeting technical specifications but also the broader contextual significance of a project within the urban landscape.
One significant risk associated with an excessive reliance on design algorithms, especially AI tools, is the erroneous belief that spatial designers can be entirely replaced, relegating them to superficial enhancements, such as façade adjustments, in computer-generated spatial layouts.
A lateral approach, often referred to as creativity, enables the human mind to generate innovative solutions. When combined with a thorough analysis of the 'hard' parameters, this approach provides more effective responses to complex and multifaceted challenges. AI can be a valuable tool for analyzing program requirements and proposing potential solutions, representing a crucial step toward comprehensive problem-solving.
It is of utmost importance for the design community to promptly emphasize and underscore this distinction, not only to the construction industry and political decision-makers but also to the general public and particularly to fellow spatial designers. The goal is not to resist this transformation but to embrace it in an informed and meaningful manner, acknowledging the unique value that spatial designers bring to the built environment.



NREP, Proposal for Okernvelen, Norway, 2020. *(bron: 'Architecture in the Age of Artificial Intelligence, An Introduction to AI for Architects', Neil Leach)*

5. Relevance

Due to mounting societal pressures, the entire construction sector's practices are under scrutiny. Whether it concerns the affordability and feasibility of construction due to economic and societal shifts, the growing emphasis on incorporating ecological considerations and circularity into the building process, the increasing demands on available land and spatial scarcity, shifts in demographic composition, or the need for alternative construction methods, the call for change in design, development, and construction is growing stronger.

Financial and temporal aspects often play an excessively dominant role in these considerations, overshadowing other, potentially more critical factors that are less quantifiable, such as quality, happiness, health, and sustainability. However, 'real estate' is not merely a means for employment or financial gain; it is an end in itself, serving the adequate housing of human activities while respecting ecology and the environment.

To meet the forthcoming changes, all parties in the construction process must reevaluate their roles and practices. For architects, urban planners, and landscape designers, this necessitates closer collaboration with other disciplines to arrive at high-quality solutions. This not only calls for the integration of fields but also, given the significantly increased complexity of programs, requires an increasing reliance on data-driven information, processed with the assistance of Artificial Intelligence. However, there is substantial resistance to 'tools' that collect data. Data in isolation are devoid of meaning; their interpretation is pivotal, and manipulation is a potential concern. The origins of data are often unclear or unrepresentative, and this issue must be addressed.

The danger of approaching design and construction issues solely from a quantitative perspective is a known risk, as history has demonstrated. Sustainable developments in spatial planning require a comprehensive approach focusing on qualitative aspects, which are not yet fully encapsulated in data-processing algorithms. This implies that the role of the designer will never be overshadowed by construction economics and hasty decision-making. A one-sided emphasis on the quantifiable alone leads to incomplete results and, consequently, societal and economic capital destruction.
Designing solely based on data means utilizing and assembling existing available information through algorithms, whereas designers seek innovative solutions that have often not been measurable previously. Creativity is frequently rooted in 'not-knowing.'

The relevance of this project becomes evident by juxtaposing these two approaches (generating from known data vs. conceiving from a lateral approach) and highlighting the indispensable role of the designer alongside data knowledge centers and algorithm programs. The project 'Of Immeasurable Importance' aims to explore the relevant connections between these seemingly different approaches with the goal of maintaining or elevating the standards of future design and construction at both quantitative and qualitative levels.

4

Appendix 1: Project Plan (cont'd)

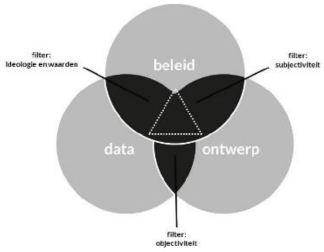
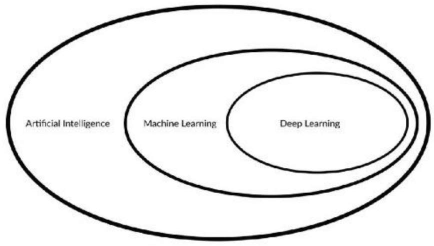


Diagram relationship AI and architect for a design



Theoretical diagram of AI (source: 'Architecture in the Age of Artificial Intelligence, An Introduction to AI for Architects' by Neil Leach).

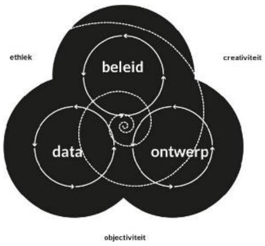


Diagram relationship AI and architect for a design

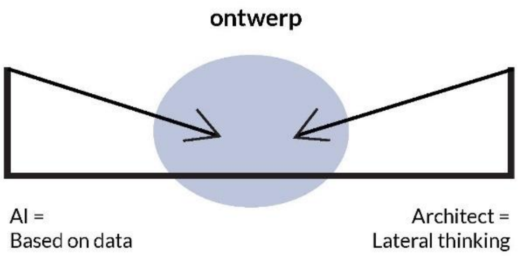
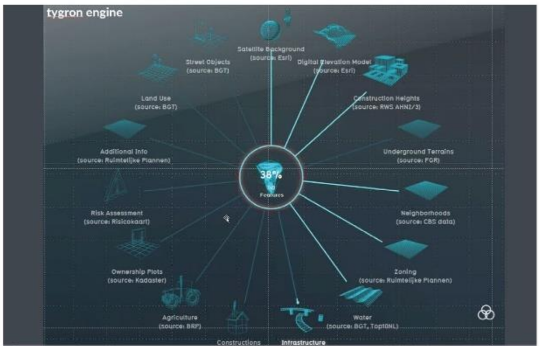


Diagram relationship AI and architect.

Diagram relationship AI and architect for a design



Tygron engine diagram: powerful means of gathering available data at a location (source: Tygron, City of the Future)

RIVM study on social effects of Rhapsody in the Kolenkit neighborhood (2021).

5

Appendix 1: Project Plan (cont'd)

6. Intended audiences

The project 'unmeasurably important' is designed to engage multiple target audiences concurrently, spanning diverse knowledge backgrounds and fields of interest. The format of the exhibition is tailored to this purpose: it should be both attractive and digestible, featuring clear statements and messages, yet also possessing sufficient depth to captivate professionals invested in the subject. In summary, the intended audiences encompass:

• **Society as a whole**: The significant construction challenge at hand must be addressed effectively. Once built, it is rarely unmade, implying that inadequacies in construction can yield problems spanning decades.

• **The designing world**: There is a pressing need for awareness of the transformations within the field and guidance on how to navigate them.

• **Administrators and politicians:** Their role is crucial in shaping rules and regulations to ensure that the design of cities and buildings remains in the hands of knowledgeable and creative designers with a strong position within projects.

• All **inhabitants and users** of the built environment: The living environment should promote social, safe, and inclusive living.

• **Educational institutions and students:** Understanding the key emphasis areas for designers and theorists of the near future is essential. Education should also maintain a clear and consistent balance between various aspects.

• **Inclusivity:** Involving all stakeholder groups is essential, spanning gender, age, education level, and nationality. Achieving this requires a profound democratization of urban intensification processes, involving transparency in development processes and making decision-making comprehensible to truly give stakeholder participation meaning. In "City of the Future," we have established a model that enables data-driven processes and democratization through a 'urban transition game' utilizing 'gamification' suitable for all levels of expertise.

Gamification for making complex decision-making manageable (Stad van de Toekomst, 2020.)

7. Approach

The objective is to provide visitors to the exhibition and lectures with insights into both sides of the issue concerning the use of AI in spatial design processes. The first facet involves understanding the soft values of buildings and urban designs and their potential hard values in terms of experiences, feelings of health, happiness, and well-being. These qualities hold value in numerous ways, such as reducing illness, lowering crime rates, fostering social bonds, and enhancing inclusivity. These soft values indirectly contribute to economic value.

The exhibition has a two-fold structure:

Unmeasurably Important: The existence of these values is illustrated in the exhibition through several key projects by Tangram, displayed in an appealing manner with models and large billboards featuring photos and text. Projects are presented through text, images, and models, each aligned with leading soft themes like "*the built environment as a catalyst for social life*" (Rhapsody in West, Amsterdam), "*high density but not high and not dense*" (Crystal Court Buitenveldert/ Campinaterrein Oudorp), "*love for life*" (Zuidoever), "*place-bound memories*" (OurDomain Rotterdam/Ambachtsplein Leiden), "*in harmony with nature*" (Waterwoningen, Osdorp/ SALEM, Katwijk), "*urban life in the building*" (Galaxy Utrecht), "*mobile yet at home/everything in its place*" (Europan I).
All of these projects are esteemed for their soft values.

Measurably Important: In contrast, the exhibition presents the ways in which designs based on data can be generated, with installations that clearly illustrate this process. Data sources include cadastral data, zoning regulations, subsurface data, noise pollution, and more.

Bringing the two together: The exhibition subsequently highlights differences in the outcomes of these two approaches. These differences are analyzed to draw conclusions for the improvement of AI design tools. This analysis will also be discussed in lectures and associated discussions. The goal is to have the above-mentioned Tangram projects conceptually redesigned using AI by students from the universities, employing the same knowledge of program of requirements, location, and other parameters, including budgeting and rental levels.

Collaborating with knowledge institutions, like for example, in Delft, Eindhoven, and Amsterdam, comprising technical scientists and a science and IT philosopher, the goal is to present these analyses clearly through words and images. The focus is on moving from claims to evidence, making the positive social and economic effects of original design decisions evident.

The significance is clear: AI is gaining a crucial role in the increasingly complex design practice and urgently needs to be brought to a sufficient level to maintain design outcomes. By linking it to well-known practical examples, the message can be effectively conveyed: only a combination of creativity and data processing with algorithms can yield results.
The target audience is broad, encompassing fellow professionals, developers and builders, policymakers, and students and instructors from knowledge institutions.

Results will be shared with the broader public through various publications.

Appendix 2: Dementia evaluation scoring methodology

Table 3. Evaluation Scores Per Design Criterion Stimulating Wayfinding for Seniors With Dementia.

Number of Possibility	Description of Possibility	Score
Criterion 1. Sequence of spaces in the house. The routing inside the house should be in the line of entrance, living room, and individual room of the resident		
Sequence I	Entrance—living room—corridor with individual rooms	+
Sequence II	Entrance—(small) corridor—living room/corridor with individual rooms	+
Sequence III	Entrance—living room/corridor with individual rooms	+
Sequence IV	Entrance—corridor with individual rooms—living room	–
Criterion 2. Location of the entrance door. The location of the entrance door should not be located at the end of the corridor; it would be better to place it alongside the wall		
Entrance position I	Alongside the corridor	++
Entrance position II	At the end of the corridor in a niche, 90 degrees turned from the end of the corridor	+
Entrance position III	In the living room	0
Entrance position IV	Entrance hallway comes out in the living room	0
Entrance position V	At the end of the corridor	–
Criterion 3. Location of the living room. The location of the living room should be placed at a remarkable place in the building, for example at the end of the corridor		
Position living room I	At the end of the corridor	+
Position living room II	Alongside the entire length of the route	+
Position living room III	At the end of the corridor, 90° turned from the end of the corridor	0
Position living room IV	In the middle—alongside—the corridor	0
Position living room V	The entrance hall separates the corridor with the individual rooms and the living room	–
Criterion 4. Visual access between entrance and the living room. Provide visual access between the entrance hall and the living room (this increases the orientation skills of the resident, the feeling of home, and a feeling of overview for both the resident and the care professional)		
Visual access I	Yes	+
Visual access II	No	–
Criterion 5. Visual access between the living room and the corridor. Provide visual access between the living room and the corridor		
Visual access I	Yes	+
Visual access II	Yes, softly separated	0
Visual access III	No	–
Criterion 6. Visual access between sanitary and individual room. Provide visual access between the door of the sanitary room from the bed in the individual room		
Visual access I and layout I	Yes and the sanitary room attached to the rectangular shaped individual room	+++
Visual access I and layout II	Yes and the sanitary room inside the rectangular shaped individual room, and the door of the sanitary room is located at the wide side of the space	++
Visual access I and layout III	Yes and the sanitary room inside the rectangular shaped individual room, and the door of the sanitary room is located at the chamfered side of the space	++

Appendix 2: Dementia evaluation scoring methodology (cont'd)

Table 3. (continued)

Number of Possibility	Description of Possibility	Score
Visual access I and layout IV	Yes and the sanitary room inside the rectangular shaped individual room, and the door of the sanitary room is located at the smaller side of the space	+
Visual access II	No, no individual sanitary room	−
Criterion 7. Length of the route. Make use of short routes in relation to orientation		
The longest route from an individual room (furthest away from the living room) to the living room will be measured. This is a quantitative dimension in meters (feet). In the evaluation, the shorter route within the comparison between two cases will be assessed as better		
Criterion 8. Width of the corridor. The corridor should be wide enough for the passage of two persons next to each other and to provide overview		
The smallest passage of the corridor will be measured; quantitative dimension in millimeters (feet). (The width of one wheelchair is 750 mm (2.46 feet), and two wheel chairs next to each other have a width of 1,500 mm)		
Width I	≥1,500 mm (4.92 feet)	+
Width II	<1,500 mm (4.92 feet)	−
Criterion 9. Shape of the corridor. Make use of articulated architecture		
Shape I	Both sides are differentiated	++
Shape II	One side niches, one side differentiated	++
Shape III	At both sides niches	+
Shape IV	One side straight, one side with niches	+
Shape V	One side straight, the other with openings to the living room (formed by interior elements)	+
Shape VI	One straight rectangular shape	−
Criterion 10. Moments of decision on the route. Decrease the amount of moments of decisions		
The amount of decision moment (which will be explained in the next line) on the longest route from the individual room (furthest away from the living room) to the living room will be calculated. Three types of decision moments can be distinguished: 1. From the individual room the choice: left or right 2. Go around the corner 3. Go through another type of space (e.g., the entrance hall) to enter the living room		
This is a quantitative dimension in number of moments of decision and in number of moments of decision. In the evaluation, the less number of moments of decision on the route within the comparison between two cases will be assessed as better		
Criterion 11. The amount of doors in the corridor. Decrease the amount of doors in the corridor		
The amount of doors in the corridor which are calculated within this criterion is defined by the following equation. "The total amount of the doors in the corridor" (minus) "The amount of doors of individual rooms in the corridor." This is a quantitative dimension. In case of two corridors within one case, the corridor with the highest amount of doors in the corridor will be evaluated. In the evaluation, the less amount of doors in the corridor within the comparison between two cases will be assessed as better		

(continued)

Appendix 2: Dementia evaluation scoring methodology (cont'd)

Table 3. (continued)

Number of Possibility	Description of Possibility	Score
Criterion 12. Activity space at the end of the corridor. Locate at the end of the corridor no individual space of the resident, but a space of activity		
Type of space I	Individual room of a resident	–
Type of space II	Individual room of a resident, turned around 90°	**0**
Type of space III	Any other type of space than an individual room of a resident	+
Criterion 13. Entrance of natural daylight. Make use of natural daylight and view outside in the corridor		
Daylight I and location I	Yes and alongside and at the end of the corridor	+++
Daylight I and location II	Yes and alongside the corridor	++
Daylight I and location III	Yes and at the end of the corridor	+
Daylight II	No	–
Criterion 14. The amount of doors in the living room. Decrease the amount of doors in the living room		
The total amount of doors in the living room will be measured. (This includes also the entrance door to the outside world—either outside in the open air or outside within the larger complex—when this door is situated inside the living room). In the evaluation, the less amount of doors in the living room within the comparison between two cases will be assessed as better		

Appendix 3: Floor plan samples of living clusters by van Buuren and Mohammadi

Table 2. Design Criteria Stimulating Wayfinding Abilities for Seniors With Dementia (Each Criterion Is Described With a Number, a Topic, a Description, a Visual, and With Sources).

Criterion	Topic	Definition	Visual	Source(s)
1	Sequence of spaces in the house	The routing inside the house should be in the line of entrance, living room, and individual room of the resident		De Vos (2011) and Nilisen & Optiz (2013)
2	Location of the entrance door	The location of the entrance door should not be located at the end of the corridor; it would be better to place it alongside the wall		Zeisel et al. (2003)
3	Location of the living room	The location of the living room should be placed at a remarkable place in the building, for example, at the end of the corridor		Nilisen & Optiz (2013) and Zeisel et al. (2003)
4	Visual access between entrance and the living room	Provide visual access between the entrance hall and the living room (this increases the orientation skills of the resident, the feeling of home, and a feeling of overview for both the resident and the care professional)		De Vos (2013), Marquardt (2011), Nilisen & Optiz (2013), and Passini et al. (2000)
5	Visual access between the living room and the corridor	Provide visual access between the living room and the corridor		Brawley (1997), Fleming & Purandare (2010), Marquardt (2011), Marquardt & Schmieg (2009), Namazi & Johnson (1991), Nilisen & optiz (2013), and Passini et al. (1998, 2000)
6	Visual access between sanitary and individual room	Provide visual access between the door of the sanitary room from the bed in the individual room		De Vos (2013)
7	Length of the route	Make use of short routes in relation to orientation		Aedes-Actiz (2018), Marquardt (2011), Nilisen & Optiz (2013), and Van Liempd et al. (2009)
8	Width of the corridor	The corridor should be wide enough for the passage of two persons next to each other and to provide overview		Passini et al. (2000) and Zeisel et al. (2003)

(continued)

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Table 2. (continued)

Criterion	Topic	Definition	Visual	Source(s)
9	Shape of the corridor	Make use of articulated architecture		Brawley (1997), Cohen & Weisman (1991), Heeg & Goerlich (2000), Marquardt (2011), Marquardt & Schmieg (2009), Netten (1989), and Passini et al. (1998, 2000)
10	Moments of decision on the route	Decrease the amount of moments of decisions		Marquardt (2011)
11	The amount of doors in the corridor	Decrease the amount of doors in the corridor		De Vos (2013), Marquardt (2011), Nilisen & Optiz (2013), and Van Liempd et al. (2009)
12	Activity space at the end of the corridor	Locate at the end of the corridor no individual space of the resident, but a space of activity		Marquardt & Schmieg (2009), Nilisen & Optiz (2013), Warner (2000), Zeisel (2001), and Zeisel et al. (2003)
13	Entrance of natural daylight	Make use of natural daylight and view outside in the corridor		Day et al. (2000), Marquardt (2011), and Zeisel et al. (2003)
14	The amount of doors in the living room	Decrease the amount of doors in the living room		Nilisen & Optiz (2013)

Legend: Entrance, Corridor, Living room, Individual room, Bathroom

Appendix 3: Floor plan samples of living clusters by van Buuren and Mohammadi (Cont'd)

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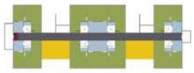
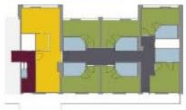
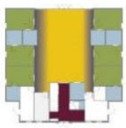
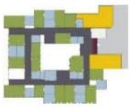
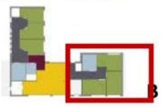
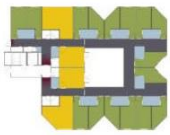
Table 5. Ranking of the 14 Cases on 14 Design Criteria Supporting Wayfinding: Overall Score.

Case Title	Floor Plan of the Living Group	Typological Floor Plan
(J) JULIANA		
(C) DE KOEKOEK		
(M) 'T LOUG		
(F) DE ZEVEN BRONNEN		
(D) DE RIETVINCK		
(A) BOSWIJK		
(E) DE SCHIPHORST		
(H.B) HOGEWEYK (B)		
(L) ST. ELISABETH		

(continued)

Appendix 3: Floor plan samples of living clusters by van Buuren and Mohammadi (Cont'd)

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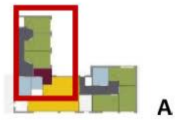
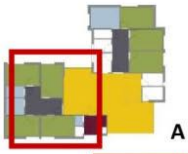
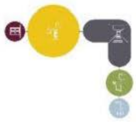
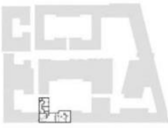
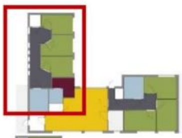
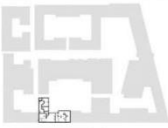
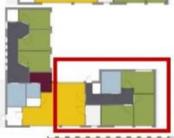
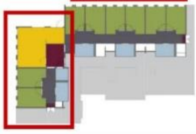
Table 5. (continued)

Case Title	Floor Plan of the Living Group	Typological Floor Plan
(H.A) HOGEWEYK (A)		
(G.A) HEIVELD (A)		
(G.B) HEIVELD (B)		
(I.A) ISSELWAERDE (A)		
(I.B) ISSELWAERDE (B)		
(N) WIJERODE		
(B) DE KEYZER		
(K) KULTURHUS LITSERBORG		

Legend: Entrance Corridor Living room Individual room Bathroom

Appendix 3: Floor plan samples of living clusters by van Buuren and Mohammadi (Cont'd)

Table 1. (continued)

Basic Information: Name, Location, Year of Completion, Architect, and Care Organization	Building Complex	Floor Plan of Living Group	# Living Groups Per Floor	# Residents Per Living Group	Principle of Circulation System	Length of the Longest Route From the Individual Room to the Living Room	Width of the Corridor at the Smallest Part	Principle of Sanitary Room
(H.A)HOGEWEYK (A)Weesp, 2009 Molenaar & Bos & van Dillen Architecten Vivium Zorggroep			16	6	Two corridors	15 m (49.21 feet)	1,599 m (5.25 feet)	Shared with >2
(H.B)HOGEWEYK (B)Weesp, 2009 Molenaar & Bos & van Dillen Architecten Vivium Zorggroep			16	6	Two corridors	15 m (49.21 feet)	1,599 m (5.25 feet)	Shared with >2
(I.A)ISSELWAERDE (A)Ijsselstein, 2013 EGM Architecten AxionContinu			4	8	Two corridors	27 m (88.58 feet)	1,476 m (4.84 feet)	Shared with 2

(continued)

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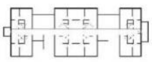
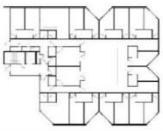
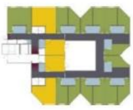
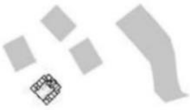
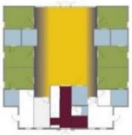
Table 1. (continued)

Basic Information: Name, Location, Year of Completion, Architect, and Care Organization	Building Complex	Floor Plan of Living Group	# Living Groups Per Floor	# Residents Per Living Group	Principle of Circulation System	Length of the Longest Route From the Individual Room to the Living Room	Width of the Corridor at the Smallest Part	Principle of Sanitary Room
(I.B)ISSELWAERDE (B)Ijsselstein, 2013 EGM Architecten AxionContinu			4	8	Two corridors	27 m (88.58 feet)	1,476 m (4.84 feet)	Shared with 2
(J)JULIANA Nijmegen, 2016 FAME Planontwikkeling ZZG Zorggroep			1	8	Linear	15 m (49.21 feet)	2,000 m (6.56 feet)	Individual
(K)KULTURHUS LITSERBORG Den Dungen, 2015 Architecten aan de Maas Brabant Wonen Vivent			4	7	Linear	21 m (68.90 feet)	1,399 m (4.59 feet)	Shared with >2
(L)ST. ELISABETH Amersfoort, 2016 Ebbens Architecten Beweging 3.0			1	16	Circular	20 m (65.62 feet)	1,552 m (5.09 feet)	Shared with 2

(continued)

Appendix 3: Floor plan samples of living clusters by van Buuren and Mohammadi (Cont'd)

Table 1. (continued)

Basic Information: Name, Location, Year of Completion, Architect, and Care Organization	Building Complex	Floor Plan of Living Group	# Living Groups Per Floor	# Residents Per Living Group	Principle of Circulation System	Length of the Longest Route From the Individual Room to the Living Room	Width of the Corridor at the Smallest Part	Principle of Sanitary Room
(M)'T LOUG Delfzijl, 2012 Wiegerinck Stichting De Hoven			4	6	Special	8 m (26.25 feet)	1,494 m (4.90 feet)	Individual
(N)WIJERODE Heerlen, 2014 DMV Architecten Mondriaan			8	10	Linear	43 m (141.08)	1,875 m (6.15 feet)	Individual

Legend: Entrance, Corridor, Living room, Individual room, Bathroom

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Appendix 4: Plan-EAT by Quirke et al

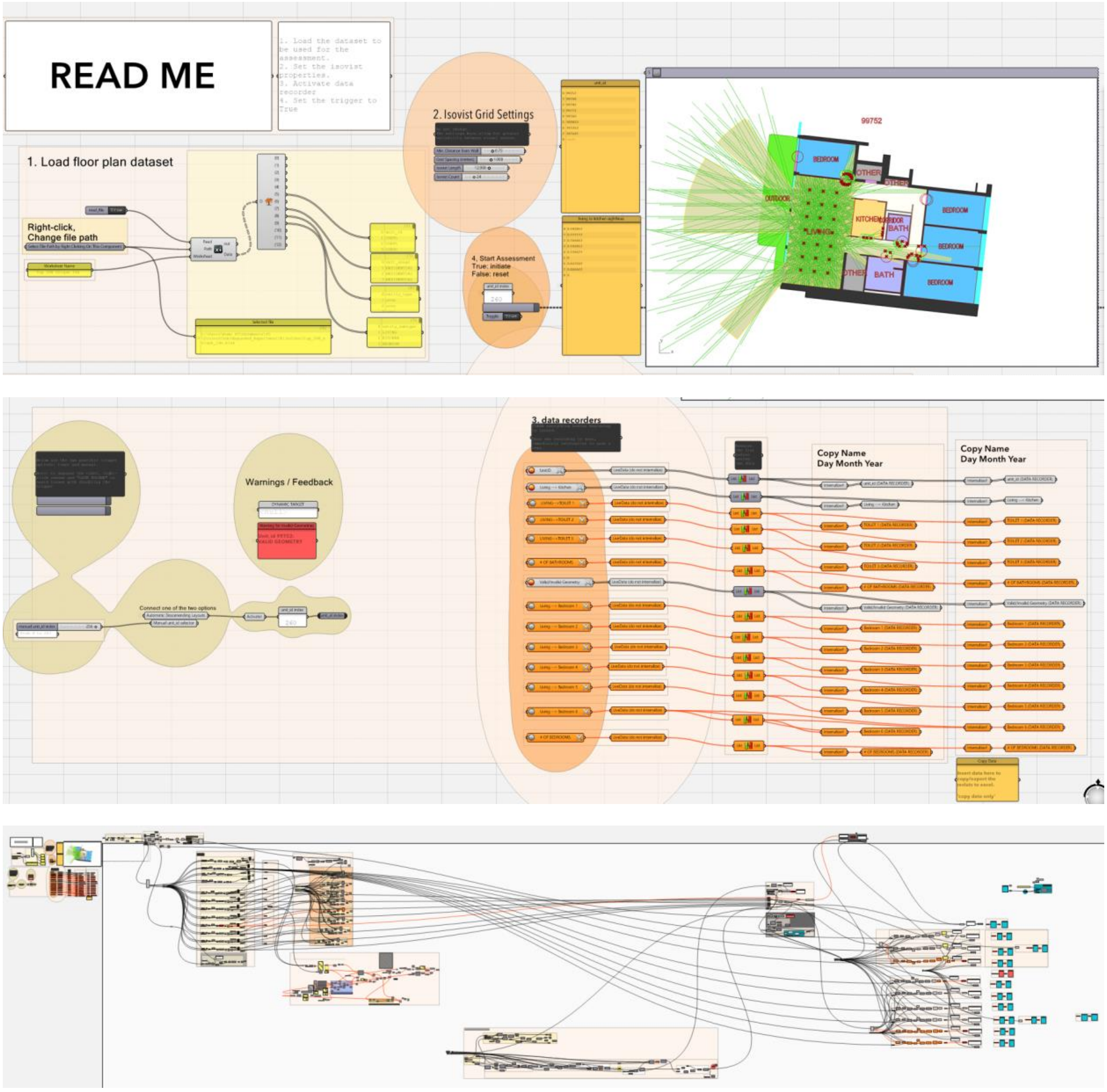
Appendix 1

		RANK LAYOUT TYPE BY PLAN-EAT SCORE		1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20	21	22	23	24	25	26	27	28	29	30	31	32	33	34		
Plan-EAT: Based on the Environmental Audit Tool (Fleming, 2011)		Facility/Layout Case Number	Max Points per query	Case 1	Case2	Case 3	Case 4	Case 5	Case 6	Case7	Case 8	Case 9	Case 10	Case 11	Case 12	Case 13	Case 14	Case 15	Case 16	Case 17	Case 18	Case 19	Case 20	Case 21	Case 22	Case 23	Case 24	Case 25	Case 26	Case 27	Case 28	Case 29	Case 30	Case 31	Case 32	Case 33	Case 34	OVERALL AVERAGE	OVERALL MEDIAN
		No. Units Represented		1	5	1	23	2	1	1	10	3	1	1	2	1	2	4	1	3	2	2	2	1	1	2	4	1	2	1	1	2	1	1	2	3	4		
		Purpose Built for Dementia?		Yes	Yes	Yes	Yes	Yes	Yes	yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	No	Yes	Yes	No	No	Yes	No		
		Garden Drawn?		Y	Y	N	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	Y	n	n	Y	Y	n	n	Y	Y	Y	N	Y	n	Y	Y	N	n	N		
		Ground or Upper Floor Unit?		Ground	Ground	Ground	Ground	Ground	Ground	Ground	Upper	Ground	Ground	Ground	Ground	Ground	Ground	Ground	Ground	Ground	Ground	Ground	Upper	Ground	Ground	Ground	Ground	Ground	Ground	Ground	Ground	Ground	Ground	Ground	Ground	Upper	Upper		
		Number of Resident Bed Spaces		9	15	8	6	12	15	20	10	20	15	30	12	11	12	16	12	16	6	8	11	12	12	16	16	12	12	24	40	16	24	76	26	40	26	18	15
Dementia Design Principle	Query No.	Plan-EAT Query Item (Score info)																																				Average	Median
1. Safety	1.05	Is the garden easily supervised from the point(s) where staff spend most of their time?	2	2	2	1	1	2	2	2	2	1	2	2	2	1	1	1	1	2	0	2	0	2	1	0	1	1	0	2	2	0	1	0	0	0	0	1	1
1. Safety	1.13	Is the lounge room easily supervised from the point(s) where the staff spend most of their time?	2	2	2	2	2	2	2	2	2	1	2	2	2	2	1	2	1	2	2	2	2	2	2	1	2	1	1	2	1	1	2	1	1	2	1	2	2
2. Human Scale	2.01	How many people live in the unit? (Max 10=3 / 11-15=2 / 16-29=1 / 30+=0)	3	3	2	3	3	2	2	1	3	1	2	0	2	2	2	1	2	1	3	3	2	2	2	1	1	2	2	1	0	1	1	0	1	0	1	2	2
3. Visual Access	3.01	What proportion of confused residents can see their bedroom door from the lounge room? (0=0 / 25%=1 / 50%=2 / 75%=3 / 100%=4)	4	1	1	3	1	3	1	1	3	2	1	0	3	0	0	2	0	1	1	4	4	1	2	3	2	1	2	3	0	0	1	0	1	3	1	2	1
3. Visual Access	3.02	What proportion of confused residents can see the lounge room as soon as they leave their bedroom? (0=0 / 25%=1 / 50%=2 / 75%=3 / 100%=4)	4	2	2	4	1	3	1	1	3	4	1	0	3	0	0	4	0	1	4	4	4	1	4	4	4	1	2	4	1	0	1	0	2	3	2	2	2
3. Visual Access	3.03	What proportion of confused residents can see the dining room as soon as they leave their bedroom? (0=0 / 25%=1 / 50%=2 / 75%=3 / 100%=4)	4	2	2	4	0	3	1	1	3	1	1	0	3	0	1	4	1	1	0	4	4	1	4	4	4	1	4	3	0	1	0	0	3	3	3	2	2
3. Visual Access	3.04	Can the exit to the garden be seen from the lounge room? (If there is more than 1 lounge room answer with reference to the one most used by most confused residents).	1	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	0	1	1	0	0	0	0	1	1	0	0	0	1	1
3. Visual Access	3.05	Can the dining room be seen into from the lounge room? (If there is more than 1 dining room or lounge room answer with reference to those used by most confused residents).	1	1	1	1	1	1	1	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1
3. Visual Access	3.06	Can the kitchen be seen into from the lounge room? (If there is more than 1 lounge room answer with reference to the one used by most confused residents).	1	1	1	1	0	1	1	1	1	0	1	1	1	0	0	1	0	1	1	1	1	1	1	1	1	1	0	1	0	0	0	0	0	0	0	1	1
3. Visual Access	3.07	Can the kitchen be seen into from the dining room? (If there is more than 1 dining room answer with reference to the one used by most confused residents).	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1	1	1	0	1	1	1	0	0	0	0	0	0	1	1
3. Visual Access	3.08	Can a toilet be seen from the dining room? (If there is more than 1 dining room answer with reference to the one used by most confused residents).	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	1	1	1	0	1	0	1	1	0	1	1	1	0	1	0	1	0	0	1	0	1	1
3. Visual Access	3.09	Can a toilet be seen from the lounge room? (If there is more than 1 lounge room answer with reference to the one used by most confused residents)	1	1	1	1	0	1	1	0	1	0	1	1	0	1	1	0	1	1	1	1	1	0	1	0	0	1	1	1	0	0	0	0	0	1	0	1	1
3. Visual Access	3.10	Can the lounge room be seen into from the point(s) where staff spend most of their time?	1	1	1	1	1	1	0	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	0	1	1	1	1	1
4. Stimulus Reduction*	4.05	Are deliveries of food, linen etc. taken across public areas such as the lounge or dining room?* (Note inverted scoring)	1	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	0	1	0	1	0	1	1	1	1	1	1	1	1
4. Stimulus Reduction*	4.07	Is the front entry to the unit easily visible to the residents?* (Note inverted scoring)	1	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	1	1	0	0	0	0	0	0	0
4. Stimulus Reduction*	4.80	Is the service entry (where food, linen etc. is delivered to) easily visible to the residents?* (Note inverted scoring)	1	1	1	1	1	1	1	1	0	1	0	1	0	1	0	1	0	0	0	1	1	1	0	1	1	1	0	0	1	1	1	0	0	0	0	1	1
5. Useful Stimulation	5.01	Is the dining room looked into from the lounge room or clearly marked with a sign or symbol?	1	1	1	1	1	1	0	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	1	1	1	1	1	1
5. Useful Stimulation	5.02	Is the lounge room either looked into from the dining room or clearly marked with a sign or symbol?	1	1	1	1	1	1	0	1	1	0	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	0	1	1	1	1	1	1
5. Useful Stimulation	5.05	Is the kitchen either looked into from the lounge or dining room or clearly marked with a sign or symbol?	1	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	0	1	1	1	1	1	1	0	1	1	1	1	1	0	0	0	0	0	0	1	1
5. Useful Stimulation	5.06	Are toilets visible as soon as the toilet/bathroom door is opened?	1	0	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	1	0	1	0	0	0	1	1	1	1	0	0	0	0	0	0	0	1	1
5. Useful Stimulation	5.07	Is there a lot of natural lighting in the lounge room?	1	1	1	0	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1	1	0	0	1	1	1	1	0	1	0	1	1
6. Provision for Wandering + Outside Spaces	6.1a	Is there a clearly defined and easily accessible (i.e. no locked exit) path in the garden that guides the resident back to their starting point without taking them into a blind alley? (If answer to 1a is YES answer 1b,1c,1d,1e,1g and 1g)	1	1	1	0	1	0	1	0	0	1	1	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	1	0	0	0	0	0	0	0	0	0	0
6. Provision for Wandering + Outside Spaces	6.1b	Does the external path allow the resident to see into areas that might invite participation in an appropriate activity other than wandering?	1	1	1	0	1	0	1	0	0	1	1	1	0	1	1	1	1	1	0	0	0	0	0	0	0	0	0	0	1	0	1	1	0	0	0	0	0
6. Provision for Wandering + Outside Spaces	6.1c	Is the path within a secure perimeter?	1	1	1	0	1	1	1	1	1	1	1	0	1	1	1	1	1	1	0	0	0	1	0	0	0	1	0	1	1	0	1	1	1	0	0	1	1
6. Provision for Wandering + Outside Spaces	6.1d	Can this path be easily and unobtrusively surveyed by staff members?	1	1	1	1	0	1	1	1	1	1	1	1	0	0	1	1	1	1	0	1	0	1	1	0	0	1	0	1	1	0	1	0	0	0	0	1	1
6. Provision for Wandering + Outside Spaces	6.1e	Are there chairs or benches along the path where people can sit and enjoy the fresh air?	1	1	1	0	1	1	0	0	0	1	1	1	0	0	1	1	1	1	0	0	0	0	0	0	0	1	0	0	0	0	1	1	0	0	0	0	0
6. Provision for Wandering + Outside Spaces	6.1f	Are there both sunny and shady areas along the path? (Reword to 'is there a choice of both Sunny and Shaded outdoor spaces' ?)	1	1	1	0	1	1	1	0	1	1	1	1	0	1	1	1	1	1	0	1	0	0	0	1	1	1	1	0	1	1	1	1	1	0	0	1	1
6. Provision for Wandering + Outside Spaces	6.1g	Does the path take residents past a toilet? (Rephrase as is a toilet available, visible, and easily accessible directly from the outdoor space?)	1	0	0	0	1	1	0	0	0	0	0	0	0	0	0	1	0	0	0	1	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6. Provision for Wandering + Outside Spaces	6.2a	Is there a clearly defined path inside that takes the resident around furniture and back to their starting point without taking them into a blind alley? (If answer to 2a is YES answer 2b)	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	0	0	1	1	1	0	1	1	0	0	0	1	1	0	1	0	1	1
6. Provision for Wandering + Outside Spaces	6.2b	Does the internal path allow the resident to see into areas that might invite participation in an appropriate activity other than wandering?	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	1	1	1	0	1	1	0	1	0	1	1
7. Familiarity	N/A	[No Plan-EAT Questions under Dementia Design Principle 7]	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
8. Privacy and Social Interaction	8.01	Are there small areas (nooks) that provide opportunities for casual interaction and quiet chats?	3	2	2	2	2	3	3	3	2	2	2	3	1	3	3	1	3	2	2	1	2	3	1	3	1	1	2	1	3	1	2	2	1	2	1	2	2
8. Privacy and Social Interaction	8.02	How many of these areas or nooks have views of pleasant or interesting scenes (outside, the living room, the nursing station)?	3	2	2	2	2	3	3	3	2	2	2	3	1	3	3	1	3	2	2	1	1	3	1	2	1	1	2	1	3	1	2	2	1	2	1	2	2
8. Privacy and Social Interaction	8.03	Do the shared living areas support small group activities (4-6 people) without re-arranging the furniture?	2	2	1	1	2	2	2	2	2	2	1	2	1	2	2	1	2	1	1	1	2	2	2	2	1	2	1	2	1	2	2	2	1	1	1	2	2
8. Privacy and Social Interaction	8.04	Does the dining room provide opportunities for residents to eat in small groups (2-4)?	2	2	1	1	0	2	2	2	1	2	1	2	1	2	1	1	1	1	1	1	1	2	2	2	1	2	2	1	2	2	2	2	1	2	1	1	2
8. Privacy and Social Interaction	8.05	Does the dining area provide opportunities for people to eat alone?	2	1	1	0	1	2	0	1	0	2	1	1	1	2	1	0	1	1	1	1	1	2	2	2	0	1	2	1	0	2	1	0	0	0	0	1	1
9. Links to Community	9.01	Is there an area or room somewhat removed from the main dining room where families can share meals with their relatives? (If answer to 1 is YES answer 1a)	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	0	1	0	1	1	0	1	1	0	0	1	1
10. Ordinary Life	10.01	Have access to a kitchen	2	2	2	2	2	2	2	2	2	2	1	1	2	1	2	2	2	1	2	1	2	2	2	2	2	0	2	2	0	0	0	0	0	0	0	1	2
10. Ordinary Life	10.07	Have constant and easy access to a lounge?	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	2	1	2	2
10. Ordinary Life	10.08	Have constant and easy access to a dining room?	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	2	1	2	1	2	2

Appendix 4: Plan-EAT by Quirke et al (cont'd)

		*DDP4 *Stimulus Reduction* is comprised of negative or unhelpful features. Scoring of related assessment items are therefore inversed such that answers in the negative are required for points to be awarded.		Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Points	Average	Median
	DDP #1	Safety	4	4	4	3	3	4	4	4	4	2	4	4	4	3	2	3	2	4	2	4	2	4	3	1	3	2	1	4	3	1	3	1	1	2	1	3	3
	DDP #2	Human Scale	3	3	2	3	3	2	2	1	3	1	2	0	2	2	2	1	2	1	3	3	2	2	2	1	1	2	2	1	0	1	1	0	1	0	1	2	2
	DDP #3	Visual Access	19	12	12	18	6	16	7	9	16	10	10	7	15	3	6	16	6	10	11	19	17	9	17	15	16	9	12	15	4	3	5	2	8	13	8	11	10
	DDP #4	Unhelpful Stimulation*	3	2	2	2	2	2	2	2	0	3	1	2	1	3	1	1	1	1	1	2	2	2	0	2	1	2	0	1	2	3	2	1	1	1	1	2	2
	DDP #5	Useful Stimulation	5	4	4	4	5	5	3	5	4	3	4	5	5	2	4	5	4	4	5	4	4	4	4	3	5	5	2	4	2	3	1	3	2	3	2	4	4
	DDP #6	Movement and Engagement	9	8	8	3	6	7	7	4	5	8	8	7	3	6	9	7	8	8	2	4	0	4	2	3	2	6	4	3	5	1	7	6	2	2	0	5	5
	DDP #8	Privacy and Social Interaction	12	9	7	6	7	12	10	11	7	10	7	11	5	12	10	4	10	7	7	5	7	12	8	11	4	7	9	6	9	8	9	8	4	7	4	8	8
	DDP #9	Community Links	1	1	1	1	1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	0	1	0	1	1	1	0	1	0	1	1	0	1	1	0	0	1	1
	DDP #10	Domestic Activity	6	6	6	6	6	6	6	6	6	6	5	5	6	5	6	6	6	5	6	5	6	6	6	6	6	4	6	6	4	4	4	4	2	4	2	5	6
				Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Score	Average	Median
	DDP #1	Safety		100.00%	100.00%	75.00%	75.00%	100.00%	100.00%	100.00%	100.00%	50.00%	100.00%	100.00%	100.00%	75.00%	50.00%	75.00%	50.00%	100.00%	50.00%	100.00%	50.00%	100.00%	75.00%	25.00%	75.00%	50.00%	25.00%	100.00%	75.00%	25.00%	75.00%	25.00%	25.00%	50.00%	25.00%	70.59%	75.00%
	DDP #2	Human Scale		100.00%	66.67%	100.00%	100.00%	66.67%	66.67%	33.33%	100.00%	33.33%	66.67%	0.00%	66.67%	66.67%	66.67%	33.33%	66.67%	33.33%	100.00%	100.00%	66.67%	66.67%	66.67%	33.33%	33.33%	66.67%	66.67%	33.33%	0.00%	33.33%	33.33%	0.00%	33.33%	0.00%	33.33%	53.92%	66.67%
	DDP #3	Visual Access		63.16%	63.16%	94.74%	31.58%	84.21%	36.84%	47.37%	84.21%	52.63%	52.63%	36.84%	78.95%	15.79%	31.58%	84.21%	31.58%	52.63%	57.89%	100.00%	89.47%	47.37%	89.47%	78.95%	84.21%	47.37%	63.16%	78.95%	21.05%	15.79%	26.32%	10.53%	42.11%	68.42%	42.11%	56.04%	52.63%
	DDP #4	Unhelpful Stimulation*		66.67%	66.67%	66.67%	66.67%	66.67%	66.67%	66.67%	0.00%	100.00%	33.33%	66.67%	33.33%	100.00%	33.33%	33.33%	33.33%	33.33%	33.33%	66.67%	66.67%	66.67%	0.00%	66.67%	33.33%	66.67%	0.00%	33.33%	66.67%	100.00%	66.67%	33.33%	33.33%	33.33%	33.33%	50.98%	66.67%
	DDP #5	Useful Stimulation		80.00%	80.00%	80.00%	100.00%	100.00%	60.00%	100.00%	80.00%	60.00%	80.00%	100.00%	100.00%	40.00%	80.00%	100.00%	80.00%	80.00%	100.00%	80.00%	80.00%	80.00%	80.00%	60.00%	100.00%	100.00%	40.00%	80.00%	40.00%	60.00%	20.00%	60.00%	40.00%	60.00%	40.00%	74.12%	80.00%
	DDP #6	Movement and Engagement		88.89%	88.89%	33.33%	66.67%	77.78%	77.78%	44.44%	55.56%	88.89%	88.89%	77.78%	33.33%	66.67%	100.00%	77.78%	88.89%	88.89%	22.22%	44.44%	0.00%	44.44%	22.22%	33.33%	22.22%	66.67%	44.44%	33.33%	55.56%	11.11%	77.78%	66.67%	22.22%	22.22%	0.00%	53.92%	55.56%
	DDP #8	Privacy and Social Interaction		75.00%	58.33%	50.00%	58.33%	100.00%	83.33%	91.67%	58.33%	83.33%	58.33%	91.67%	41.67%	100.00%	83.33%	33.33%	83.33%	58.33%	58.33%	41.67%	58.33%	100.00%	66.67%	91.67%	33.33%	58.33%	75.00%	50.00%	75.00%	66.67%	75.00%	66.67%	33.33%	58.33%	33.33%	66.18%	62.50%
	DDP #9	Community Links		100.00%	100.00%	100.00%	100.00%	0.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	0.00%	100.00%	0.00%	100.00%	100.00%	100.00%	0.00%	100.00%	0.00%	100.00%	100.00%	0.00%	100.00%	100.00%	0.00%	0.00%	76.47%	100.00%
	DDP #10	Domestic Activity		100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	100.00%	83.33%	83.33%	100.00%	83.33%	100.00%	100.00%	100.00%	83.33%	100.00%	83.33%	100.00%	100.00%	100.00%	100.00%	100.00%	66.67%	100.00%	100.00%	66.67%	66.67%	66.67%	66.67%	33.33%	66.67%	33.33%	87.75%	100.00%
		Overall Plan-EAT Score		85.97%	80.41%	77.75%	77.58%	77.26%	76.81%	75.94%	75.34%	74.24%	73.69%	72.92%	72.66%	71.94%	71.66%	70.78%	70.42%	69.98%	69.09%	68.46%	67.90%	67.24%	66.67%	65.44%	64.60%	58.04%	57.14%	56.55%	55.55%	53.17%	48.97%	47.65%	40.30%	39.89%	26.72%	65.55%	69.54%

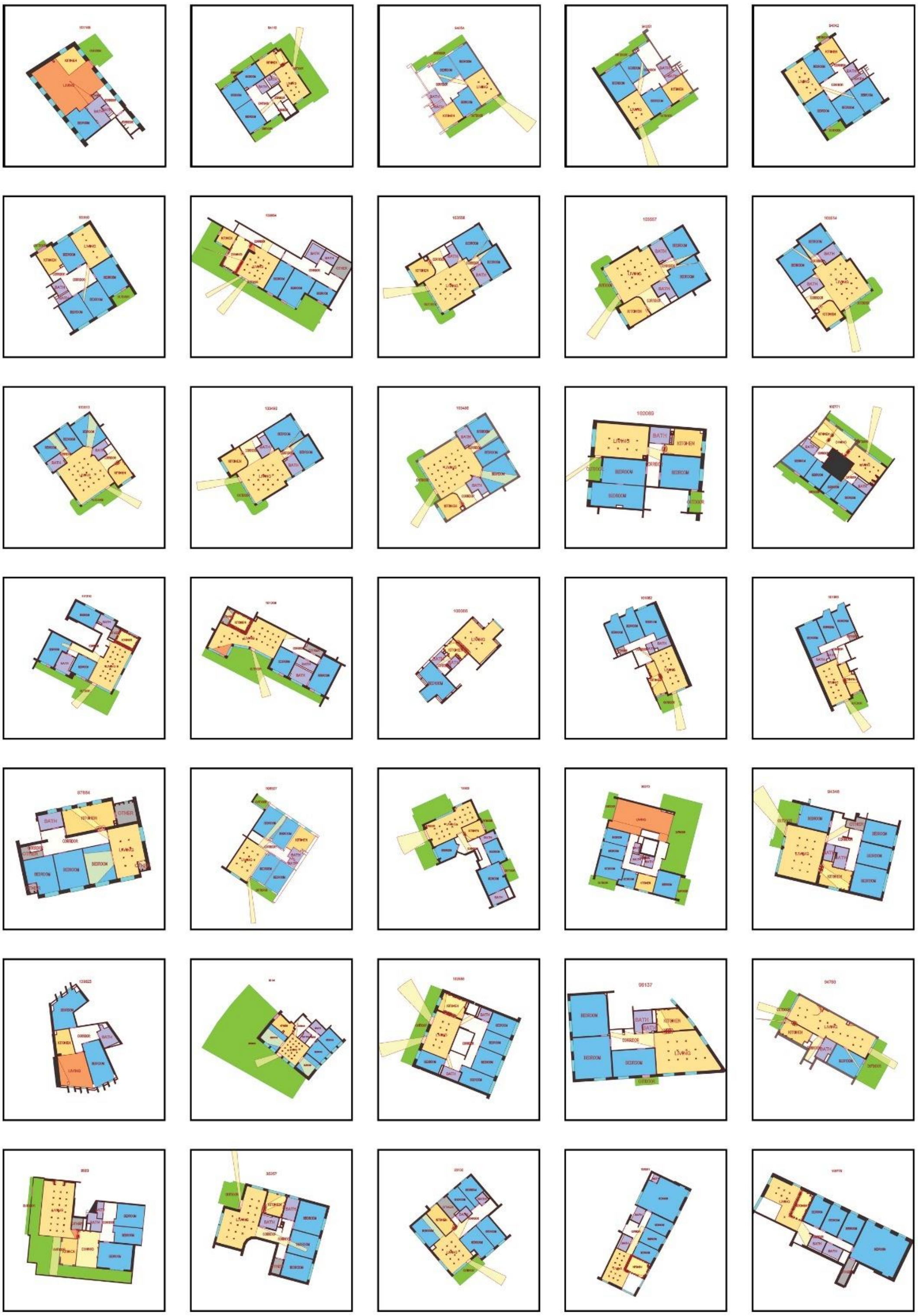
Appendix 5: Grasshopper Assessment Script



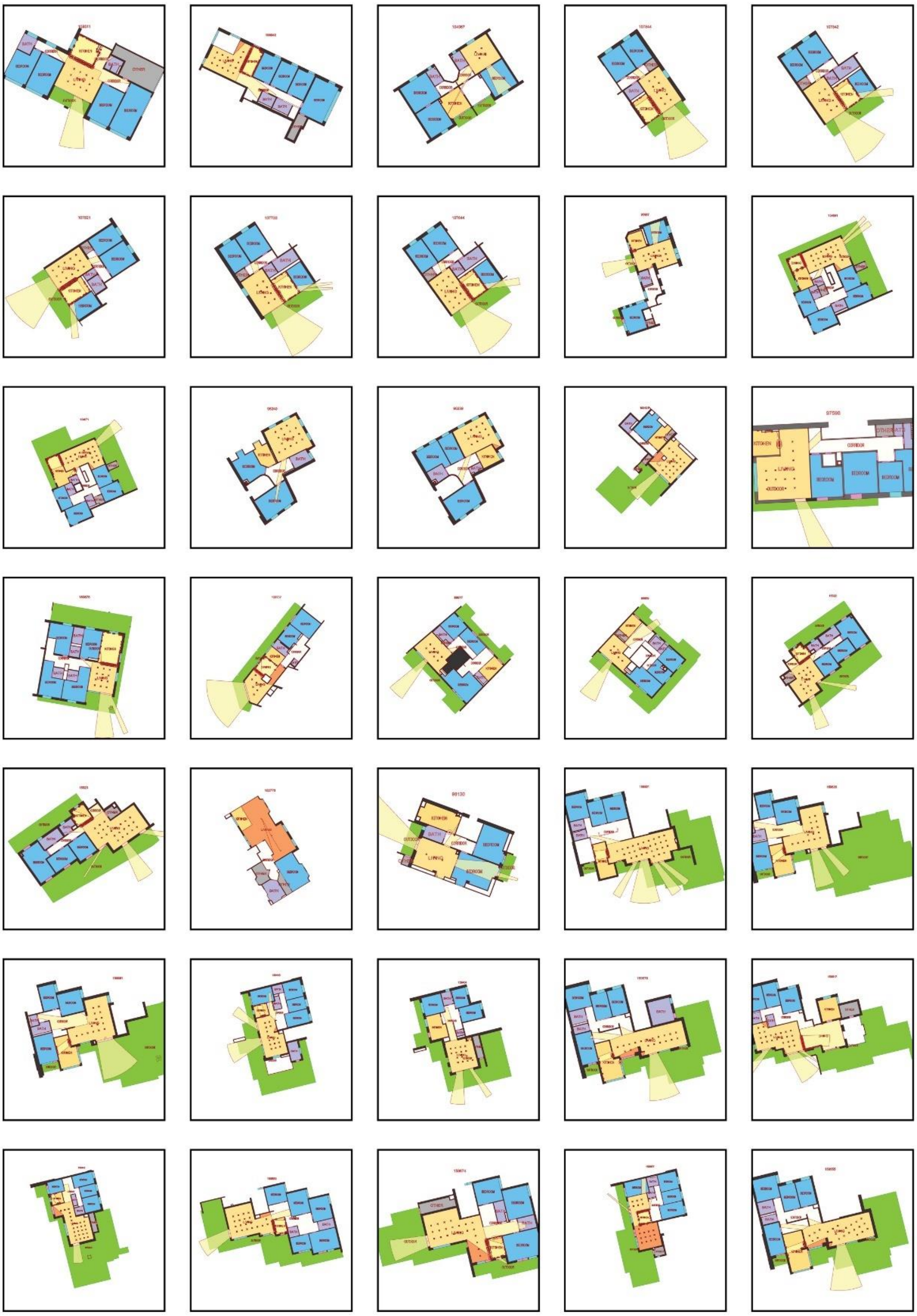
Full script available here: https://github.com/ferasongithub/Dementia-Friendly_Wayfinding_Assessment

Appendix 6: Training Dataset from the Swiss Dwellings

Appendix 6: Training Dataset from the Swiss Dwellings (cont'd)



Appendix 6: Training Dataset from the Swiss Dwellings (cont'd)



Appendix 6: Training Dataset from the Swiss Dwellings (cont'd)

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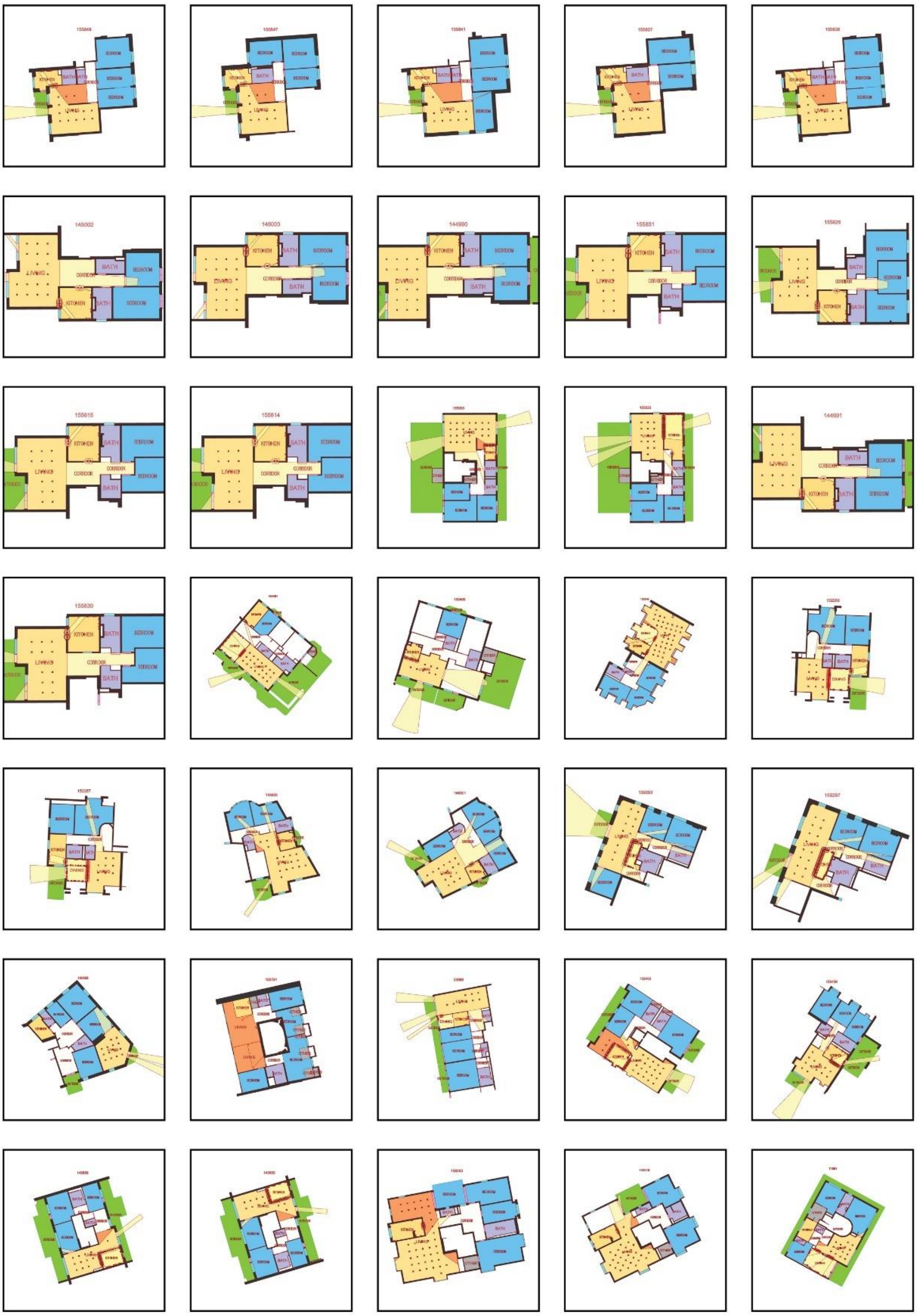

Appendix 6: Training Dataset from the Swiss Dwellings (cont'd)

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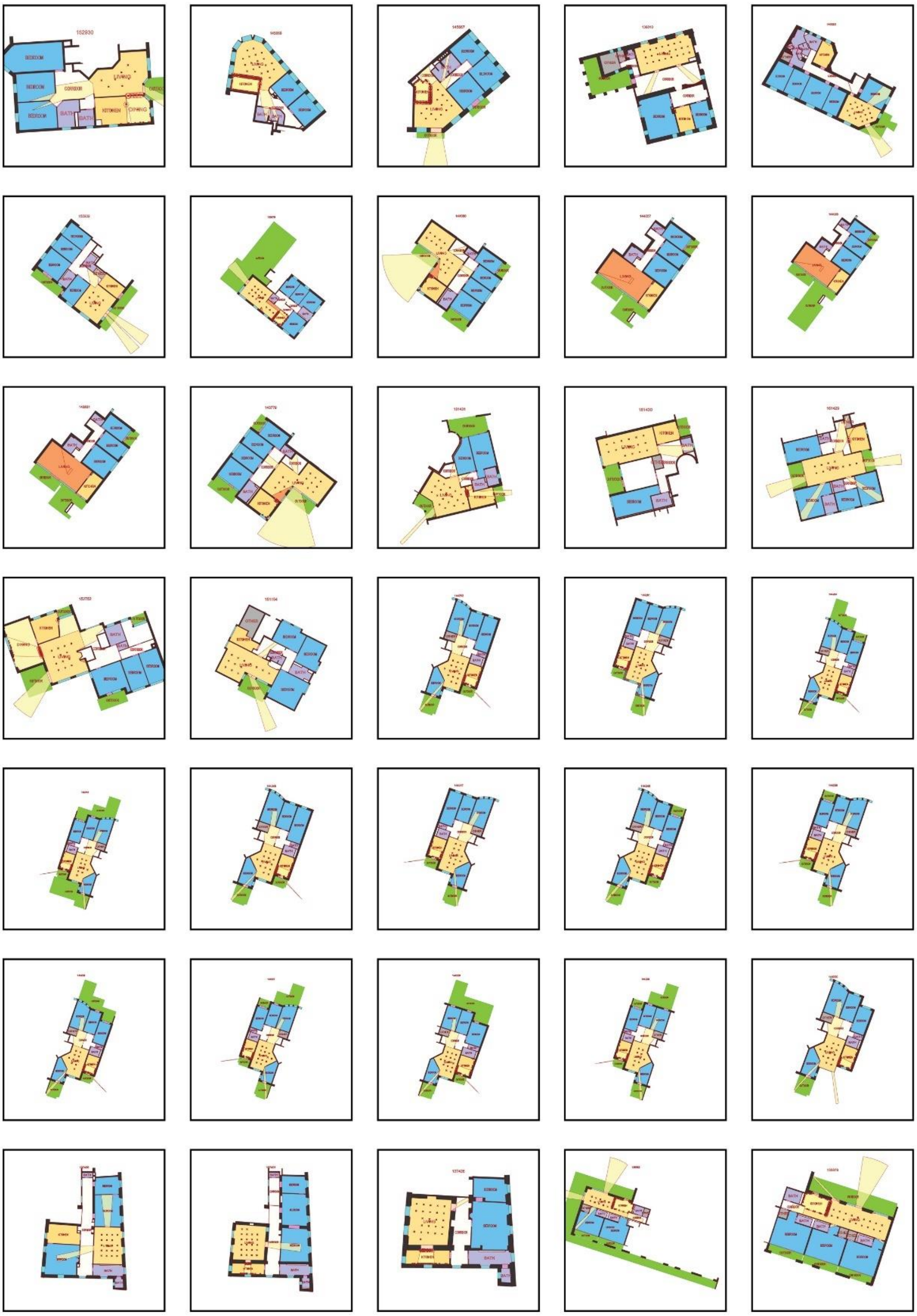

Appendix 6: Training Dataset from the Swiss Dwellings (cont’d)

DEMENTIA-INCLUSIVE DESIGN

Machine-Learning Assessment Tool for Evaluating Indoor Wayfinding Quality in Dementia Care Spaces

Published in 4 July 2024