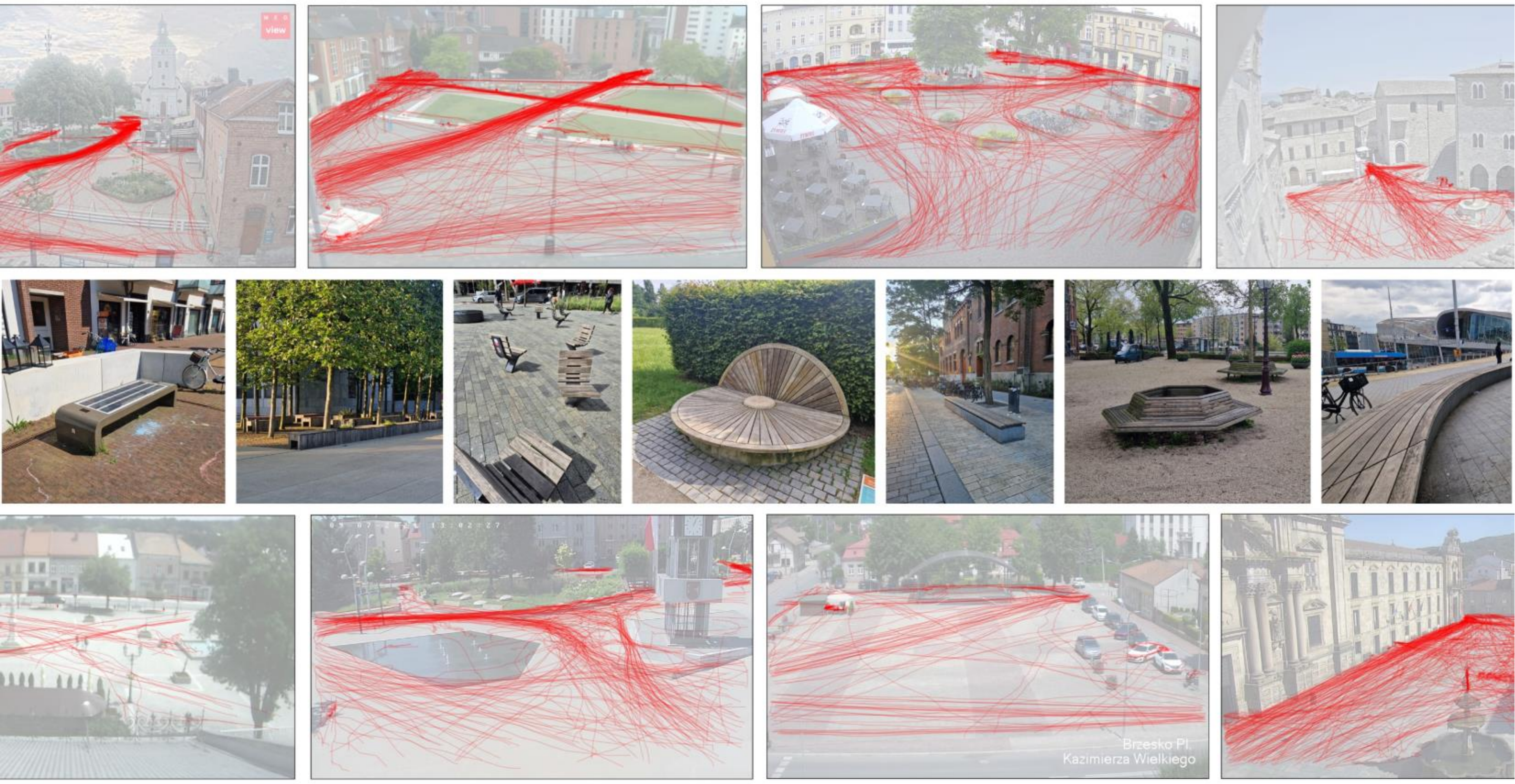
Street Seating for Vital Places

Quantifying the impact of street seating on place vitality utilizing trajectory-based vitality metrics



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Abstract

Urban public spaces are crucial to both cities and their citizens, offering places to meet, spend time outdoors, rest, and engage in various activities. Street seating like benches and chairs are seen as key elements in designing good public places. Nevertheless, the impact of spatial elements on the use of public places has been mostly assessed from the qualitative perspective. This research aimed to quantify the impact of street seating on a vitality measure for public spaces by studying 39 European public places, filmed during four different timeslots. Using object detection algorithms, a vitality score was calculated based on pedestrian trajectories. Seating attributes – including variety, edge effect, and socio-petal configurations – were collected and correlated with the vitality scores. Place characteristics, such as size, weather, and the presence of cafés or fountains, were also gathered to control for external factors. Resulting from the correlation and multiple linear regression analysis, no significant impact of street seating on the place vitality could be observed. Seating attributes with a weak positive correlation were the edge effect, the variety of seating and socio petal seating configurations. The results highlight the need for holistic approaches to public space design and call for refined vitality metrics that consider user experience and place pleasantness. The research also demonstrated the scalability and effectiveness of automated, trajectory-based vitality assessment, offering a promising tool for future urban studies.

Keywords: *Public places, Street seating, Place vitality assessment, Computer vision*

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1 Introduction

Good public places are seen as crucial for the social and psychological health of urban communities and citizens (Braun & Malizia, 2015; Carr et al., 1991; Mehta, 2014). By creating a sense of community, social interactions and attachment to a space, places can contribute to: i) more democratic societies (Carr et al., 1991); ii) the mental health of citizens (Allahdadi, 2017; Braun & Malizia, 2015; Brown et al., 2014; Goosen & Cilliers, 2020; Mehta, 2014); iii) decrease in crime (Jacobs, 1961; Jacobsen & Avi-Itzhak, 1978; Noël & Dardenne, 2024) and iv) higher satisfaction with the neighborhood (Francis et al., 2012). After this has been neglected for multiple decades, urban planners once again recognized the importance of place attachment and local communities for cities and citizens in the mid-20th century (Alexander, 1977; Jacobs, 1961; Lynch, 1960). As a result, detailed observation of human behavior and place use was incorporated into the planning routine (Gehl, 1987; Shaftoe, 2012; Whyte, 1980). Place vitality is seen as one of the main elements of functioning public spaces. This is because vitality can affect safety, mental support, and community building (Gehl, 2013; Jacobs, 1961; Walljasper, 2007; Whyte, 1980). It is therefore seen as one of the key indicators for analyzing public spaces, such as streets, parks, and places (Gehl & Svarre, 2013).

1.1 Background

Urban planners and citizen groups enhance public spaces with street furniture (SF) to increase the vitality and social sustainability of spaces. SF ranges from fixed or moveable seating over streetlamps up to waste bins (Lesan & Gjerde, 2021). It can be placed by grassroots movements or by authorities. Also, SF is often organized in the temporary shape of tactical urbanism (e.g. street experiments) (Lydon & Garcia, 2015) but is also planned as fixed elements of the public space for desired functions such as comfort, safety, or mobility (Oram et al., 2018).

Street furniture promotes an environment that invites citizens to be in nature, socialize, walk, be active, and build relationships with places and people when being places successfully (Gehl, 2013; Lesan & Gjerde, 2021; Paydar & Kamani Fard, 2021). An example is moveable chairs that allow any possible seating configuration for socializing or being alone (see Figure 1-1). Next to these "social" purposes, street furniture can also be used to control crowds or to avoid "unwanted behavior" such as littering or sleeping (Feldman et al., 2013). The "Camden bench" (see Figure 1-2) is an example of street seating used to avoid various "undesired behaviors" such as sleeping or skating.

Figure 1-1: Moveable chairs in the park Jardin du Luxembourg in Paris allow any seating configuration (Parisperfect, n.d.).

Figure 1-2: The "Camden bench": Designed to avoid sleeping, long sitting, and other "undesired behaviour" (Science Gallery, 2012).

Planning guidelines and scientific research about public places put street furniture for seating at the core of furnishing public space (Gehl, 2013; Jacobs, 1961; Main & Hannah, 2009; Walljasper, 2007; Whyte, 1980). Each of them highlighted the importance of seating for an active city and to promote a feeling of togetherness. Walljasper (2007) described how street seating is the best place-element to create vital, safe, and fun places that support an active community. Whyte (1980) promoted the need for physically and socially comfortable seats that give options to choose from. Others pinpointed the positive impact of street seating on human interactions (Gehl, 2013) and the inclusiveness of public places (Mehta, 2014). Main & Hannah (2009) concluded, that the main functions of seats are resting, watching, socializing, and eating. Each of these functions is affected by the design, orientation, and surroundings of the furniture (Lesan & Gjerde, 2021).

1.2 Problem Statement

Despite knowledge about the positive impact of street furniture on the vitality of places, European cities still often lack configurations of seating that support togetherness and place vitality (European Commission, 2020; PPS, 2004). Research has shown that seating in many places is either unused or only minimally utilized. This might reduce the use of these places resulting in underused public places instead of supporting the social and psychological needs of communities (Gehl, 2013; Hwang & Lee, 2020; Lesan & Gjerde, 2021; Madanipour, 2004; Shaftoe, 2012; Smeds & Papa, 2023). A better understanding of the impact of street seating on place vitality is therefore crucial to designing public spaces for its users rather than for technical functions.

Researchers like Low et al. (2019), Whyte (1980), and Gehl & Svarre (2013) proposed manual methods of tracking humans in a place with pen and paper, making notes about every individual, and counting people. While these methods already have led to a better understanding of public places, the qualitative and manual approaches have their limits. Mehta (2014) described the general need for a quantitative evaluation of public places. Gehl & Svarre (2013) highlighted the complexity of being an observer without taking part in the event. They also described the challenges of tracking people in busy places with these manual methods and pinpointed the effort of these methods. Furthermore, research highlighted the limits of observing parallel events in public places (Smeds & Papa, 2023).

Researchers have recently developed various methods that extract information about place use from place videos (Ceccarelli et al., 2023; Hou et al., 2020; Ibrahim et al., 2020; Loo & Fan, 2023; Niu et al., 2022). By utilizing computer vision algorithms, the position and trajectories of place users were extracted. Researchers analyzed various place attributes with these trajectory-based methods. Ceccarelli et al. (2023) analyzed the dwell time of place users and the number of people to learn more about the distribution of people in a place Hou et al. (2020) quantified the use of small public places by algorithmically counting people. Other researchers also utilized the shape of the trajectories: Loo & Fan (2023) identified group sizes based on common movement patterns and derived information about social interactions and the impact of spatial elements on these. Also Niu et al. (2022) analyzed the shape of trajectories to extract the diversity and complexity of the use of public places to create a novel vitality score. However, the scalability of automated place assessment methods has not yet been utilized to learn about the impact of specific spatial elements on the vitality of public places.

1.3 Research Objective

This research aims to utilize these trajectory-based vitality metrics to overcome the challenges of resource-heavy and location-specific manual data collection. The algorithmic approach allows to quantify the vitality of public places on a large scale and within the timeframe of a master thesis.

The quantitative approach adds to the academic discourse by increasing the understanding of the impact of street seating on public places and their users. By exploring different configurations of street seating, this research aims to improve urban planning and the effectiveness of urban design and street seating specifically for a vital city. Compared to existing research about the impact of street seating on the place vitality (Main & Hannah, 2009; Whyte, 1980; Zacharias et al., 2004), this research specifically adds to the discourse by evaluating quantitatively a wide variety of public places in the European context.

This research aim ultimately leads to the main research question and four sub-research questions of this report:

RQ: What is the impact of street seating configurations on a quantitative vitality measure for public places across Europe?

> **SRQ1**: What street seating configurations are identified in the literature as affecting the vitality of public places?
>
> **SRQ2:** Which place observation methods are relevant for place assessment and how can they be applied for the analysis of European public places?
>
> **SRQ3:** Which algorithms are available for human trajectory extraction and can be applied in this research for location vitality analysis?
>
> **SRQ4:** Which metrics of location vitality are identified in existing literature and can be applied for this research?

1.4 Scope

This research will be conducted within the European context. Public places are defined as open, accessible urban plazas and squares, excluding streets, parks and private spaces. Place observations will be only executed during the summer months and dry weather conditions. In this research, one vitality score will be employed, and a clearly defined set of seating metrics will be analyzed. Seating metrics and place attributes that depend on the presence of an observer in a public space cannot be included in this research. This will exclude factors like the perceived atmosphere, comfort, safety, noise, and other factors that might influence the place vitality during the research. By including specific spatial features and place metrics, this research will aim to account for various elements that can have an impact on the place vitality. Features that will be included are e.g. the weather of the observation, the place size, and the presence of cafés and fountains.

1.5 Reader's Guide

This thesis is structured as follows: **Chapter 2** outlines relevant theories from literature relevant to place- and seating assessment specifically focusing on the vitality of public places. **Chapter 3** describes the methodology used for the seating assessment, the place observation, trajectory extraction, and vitality scoring finishing with information about the performed correlation analysis and providing details about the steps of data processing. **Chapter 4** answers the research questions by providing the results from the place and seating assessment, trajectory extraction, and vitality scoring. Ultimately, the results of the statistical analysis aim to answer the main research question. The limitations, contributions, and reflections of this research are discussed in **Chapter 5**. **Chapter 6** summarizes the research.

2 Theoretical Framework

This research will be based on the theory of public places (Chapter 2.1). It will be split into two theoretical frameworks. The first theoretical framework will be the theory of sensing place vitality (Chapter 2.2) elaborating on the importance of place vitality and different methodologies for the vitality assessment. The second theoretical framework will be street seating assessment theories (Chapter 2.3).

2.1 The Theory of Public Places

The theory of public places can be seen as a human-centered approach to urban planning (Gehl, 2013; Grantham & Tuan, 1978; Switalski et al., 2023). It is often linked back to the fundamental theories of Jane Jacobs about the use of public spaces and their contribution to a good city (Jacobs, 1961). Building upon this “new” understanding of urban planning, researchers like William H. Whyte, Jan Gehl, and Henry Shaftoe have created influential planning guidelines for urban public places (Gehl, 2013; Shaftoe, 2012; Whyte, 1980). A relatively contemporary theory of creating and changing public spaces is the term “placemaking”. Placemaking is built on the understanding that urban spaces can be transformed into urban places by considering the community as an important element of the planning process and life of a place. Jan Gehl (2013) summarized the need to consider people as a part of public spaces as the “human dimension”, Grantham and Tuan (1978) described, how the physical location “space” becomes a social space by experience which makes it a place. Each theory has in common, that the meaningfulness of places emerges from interaction of citizens with and within these spaces.

Choosing the place theory as the theoretical framework, this research ensures that humans are at the center of the research. This is fundamental for analyzing relevant elements and configuration in the public place while keeping a holistic view on the “location vitality”. It also underscores the need to consider social aspects in technical approaches.

2.2 Theory of Place Vitality

A vibrant urban life is seen to promote better health and safety in public places (Braun & Malizia, 2015). Urban vitality is therefore seen as a relevant metric to assess how well public places work (Gehl & Svarre, 2013; X. Li et al., 2022; Y. Li et al., 2022; Liu et al., 2022; Shaftoe, 2012; Whyte, 1980). Nevertheless, researchers use very different indicators for the assessment of urban vitality. This chapter aims to give an overview of the understanding of these definitions and summarizes the key points of the vitality metrics for this research.

Already early urban research as done by William H. Whyte in US cities (Whyte, 1980) tried to quantify the use of public places to learn more about public place elements and their impact on the place's vitality. He observed metrics such as the number of people, the distribution of people, or the distribution of sunlight in the place. He used this information to advise on the crucial elements of “working” public places. Ultimately, he mixed quantitative methods, such as counting, with qualitative methods, such as the description of emotions and atmosphere. By dividing the places into grid cells, he learned about the exact use of public places and their elements. At the same time, this study greatly relied on the good observational skills of the researchers, their presence in the place, and manual tracking of people.

Gehl & Svarre (2013) followed a similar approach for European cities three decades later. Their approach to learning about the vitality of places was mainly driven by observational quantitative and qualitative metrics. Counting people was seen as a great way to compare places and situations, describing the movement patterns of people and their spatial distribution was used to identify key elements of the public space. Furthermore, they analyzed the walking speed and the stay time of people. The assumption was that places where people do more than necessity activities (lingering, standing, sitting instead of just "passing by") are attractive for the users and therefore "good" places. For an in-depth analysis of public places, they proposed tracking (walking behind place users) and observation of people and their use of public places. For the specific place observation methods, Gehl & Svarre but also William H. Whyte highlighted the need to consider duration, time, and circumstances to achieve generalizable observation results about the use of public places.

Next to these metrics describing physical indicators for the place analysis, other classical researchers highlighted the need to also include the psychology of a place. Included elements were the assessment of safety, comfort, and vitality (Alexander, 1979; Lynch, 1960). Montgomery (1998) highlighted the attributes of good public places as shown in Figure 2-1 to emphasize the importance of connecting activities in a place, the image (perception of the place), and the urban form of cities and public places to create vital environments.

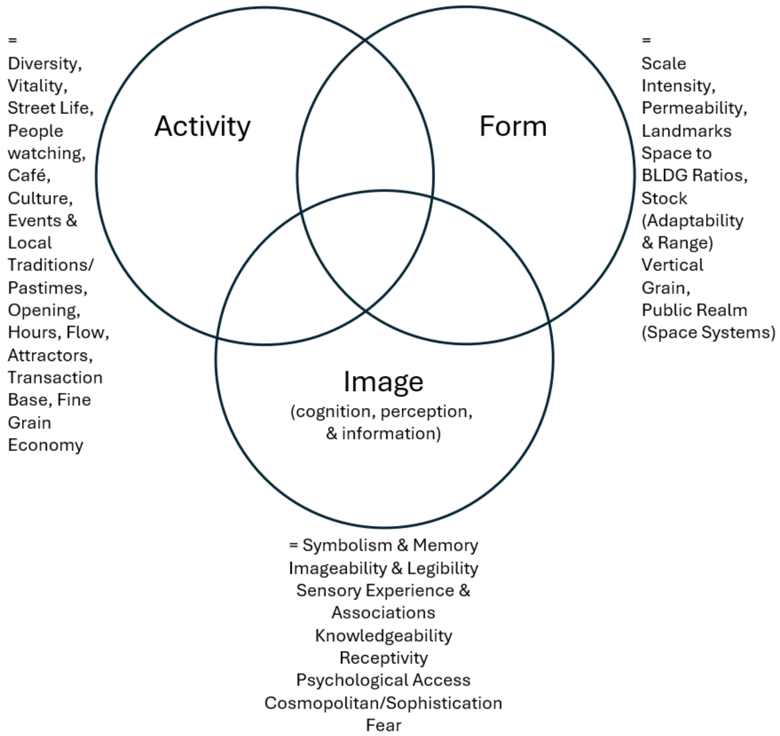


Figure 2-1: Policy directions to foster an urban sense of place (Montgomery, 1998).

Many contemporary researchers have developed methods and metrics to analyze vitality on different scales. On the city level Liu et al. (2022) described vitality with high diversity (economically, culturally, or architectural), good mobility (of population and goods, but also accessibility and the efficiency of the government), and the growth of the city (economic development, building increase, population growth…).

On the neighborhood scale, researchers assesd vitality based on various qualitative metrics. X. Li et al. (2022) counted the number of vehicles and pedestrians and the check-ins in social media as a metric that indicates people's interest. Montgomery (1998) underlined the impact of small business activities, the frequency of cultural events, or the uptake of facilities. Chen et al. (2021) analyzed the number of points of interest (POIs. E.g. museums, restaurants, or art), mobile phone check-ins, and nighttime light data to predict urban vitality in cities. Also Fang et al. (2021) used the density of POIs combined with the mix of functions, housing prices, and other metrics to describe urban density as the main element of urban vitality. Combined with social network-based locations, Gao et al. (2017) used POIs to learn more about the distribution of vital regions.

Researchers also have aimed to extract vitality information on the street and place scale. They aimed to learn more about the number of people, their duration of stay, and the diversity of activities mostly based on the public place theory of Whyte and Gehl. Y. Li et al. (2022) utilized deep learning methods to predict street vitality based on data about people walking, sitting, or standing. They specifically highlighted the reliability and scalability of their big data approach as a vitality metric. Zacharias et al. (2004) extracted the impact of microclimate and spatial elements on the vitality of places solely based on the number of people. Ceccarelli et al. (2023) used a tracking-based algorithm to analyze where people move in a place and used this methodology to learn about the impact of a place redevelopment. Their main metric was the cumulative dwell time. Also, Loo & Fan (2023) utilized tracking-based algorithms to analyze group sizes and the distribution of users in a place. With a similar approach, Niu et al. (2022) created a vitality score for the scoring of small public places. Next to the count of users and their duration of stay, they also extracted information about the diversity and complexity of activities based on the shape and similarity of trajectories. Others have analyzed street-view images or video footage on eye level to extract information about the activities in a place (Argota Sánchez-Vaquerizo & Cardoso Llach, 2019; Garrido-Valenzuela et al., 2023; L. Wang & He, 2023).

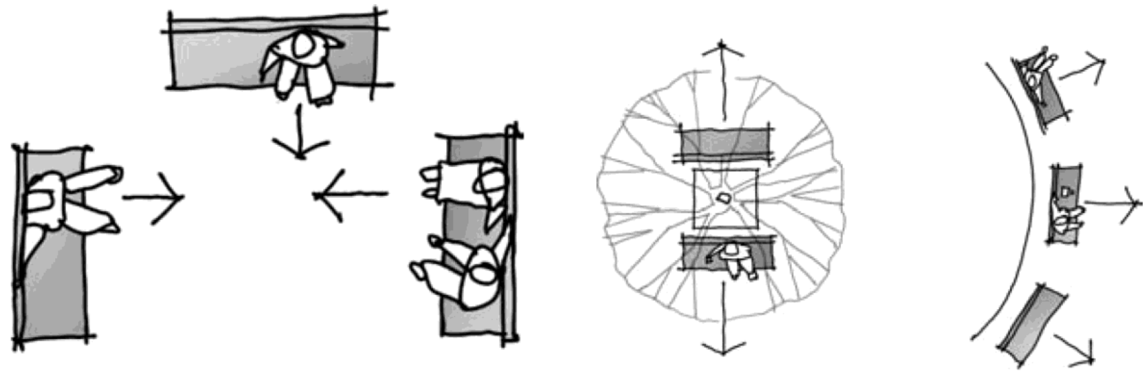
2.3 Theory of Street Seating

Street seating is seen as one of the main elements of public places contributing to vital places (Gehl, 2013; Main & Hannah, 2009; Walljasper, 2007; Whyte, 1980). It allows people to rest, do people watching, eat, meet, read, and many other activities (Lesan & Gjerde, 2021; Main & Hannah, 2009; Mehta, 2014). Public place research highlights multiple basic guidelines that make street seating appealing to users. Ultimately, these theories link back to human psychology:

- **The prospect of refuge:** Like in nature, humans are also looking in the urban context for places where they know their back is being protected while having a good overview of the place. This was first introduced by Christopher Alexander (1977) as “edge effect” and further described by Gehl (1987) and Whyte (1980). Later public place research like done by Gehl & Svarre (2013) or Main & Hannah (2009) included these observations and supported the argument, that street seating is more frequently used when complying with the theory.

- **Options of choice:** In his research on US plazas, William H. Whyte (1980) observed that the main factor of comfort for seating is not only physical comfort, but also the social comfort. Socially comfortable seating is seen as a place where users have the choice to sit where they want to sit: Alone or in groups, in the shadow or sun, on the side of places, or on the middle. Whyte observed a much better use of places that offer these options to choose from.

- **Social seating:** To attract groups and social activities to public places, Main & Hannah (2009) suggested promoting seating that allows human interactions (“socio petal” configurations) by placing seating inwards facing: A user would look into the face of other users (See Figure 2-2). Seating that is oriented outward-facing is defined as “socio fugal” and doesn’t allow interaction between the seating users. Lesan & Gjerde (2021) quantified and supported these arguments in a study about street furniture for sidewalks.



a) Socio petal seating b) Socio fugal seating

Figure 2-2: Socio petal seating (a) is designed for social interactions, while socio fugal seating is outward facing and doesn't support social interactions (Main & Hannah (2009).

Seating that follows these basic principles also supports other main activities of users of the public space. Researchers (Gehl, 2013; Shaftoe, 2012; Whyte, 1980) observed the need of public space users for "people watching". Main & Hannah, (2010, p. 52) concluded that already "the modest form of contact of merely seeing and hearing […] others" is one of the most rewarding activities in the public space. Furthermore, the option of choice can be supported with moveable chairs, wide benches that allow any sitting direction, comfortable benches with leaning or just broad steps that allow a wide variety of functions (Shaftoe, 2012; Whyte, 1980).

3 Methodology

The methodology of this research is a mixed methodology approach with the theoretical understanding of place theory, vitality, and seating on one side and a computational trajectory extraction and analysis on the other side. The methodology of this research is organized based on the research questions. A general overview of the methodology is presented in Figure 3-1. The theory of street seating assessment was used to create a seating database for each place considering relevant attributes of street seating (Chapter 3.1.1). For the observation of public places, webcams were recorded at various timeslots following classical place observation theory (Chapter 3.1.2). Object detection and tracking algorithms were used to extract trajectories of place users (Chapter 3.2). Based on these trajectories, the vitality metrics were applied to calculate a vitality score for each observation period (Chapter 3.3). Ultimately, the main research question was answered by correlating the vitality scores to seating configurations to identify the impact of different street seating configurations on the location vitality for European places (Chapter 3.4).

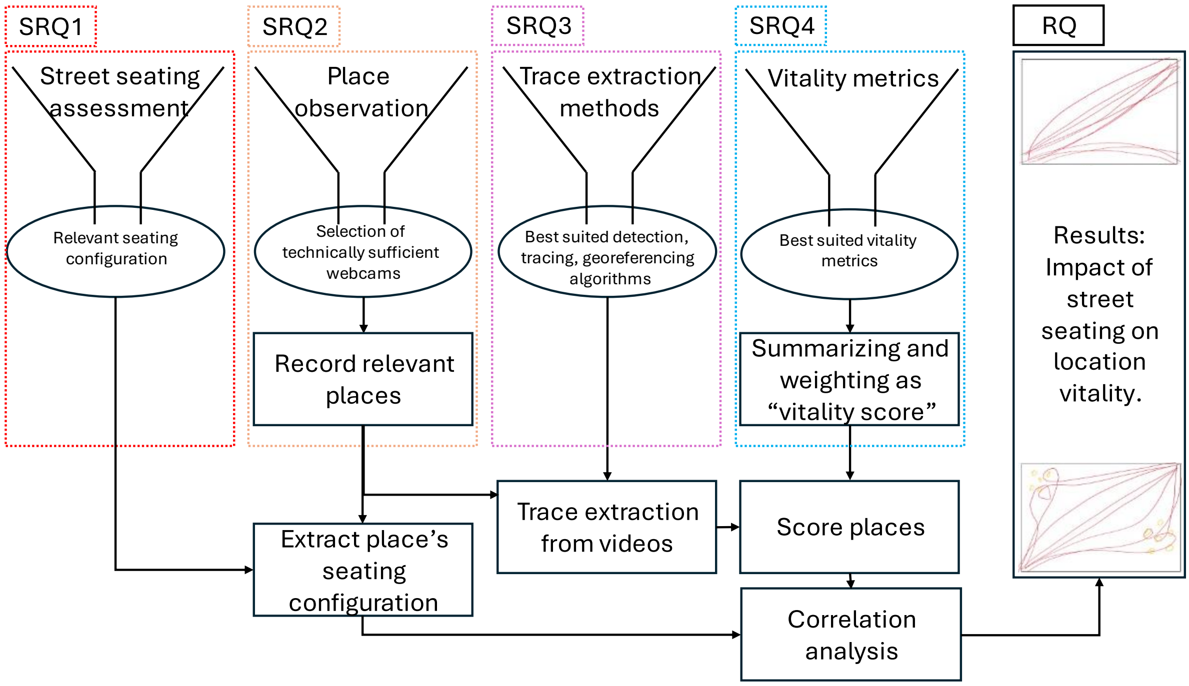


Figure 3-1: SRQs one to four are answered through literature reviews and applied in the methodological framework by collecting and analyzing place and seating data. The outcomes are used for a correlation analysis aiming to answer the main research question.

3.1 Data Collection

To explore the impact of street seating on the vitality of public places, this research created three sets of data (See Figure 3-2). Firstly, existing street seating and its relevant attributes were extracted for each observed place. Secondly, a clear understanding of the places and their specifications was needed for a good observation. Thirdly, places were filmed for a trajectory-based vitality scoring.

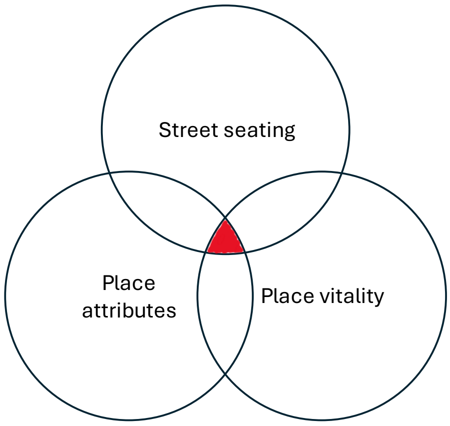


Figure 3-2: The impact of street seating on the place vitality can be identified by combining knowledge about place vitality, street seating and about the physical attributes of a place.

The data collection followed a literature review of the theory of public places, vitality assessment, street seating assessment and the observation of public places. Chapter 2 summarizes the main outcomes of this literature review. This chapter gives an overview of the applied observation methods. Chapter 3.1.1 describes the methods of street seating assessment and data collection of seating attributes based on the theoretical framework as summarized in Chapter 2.3. Chapter 3.1.2 describes which methodologies are applied for the observation and data collection of public places.

3.1.1 Street Seating Assessment

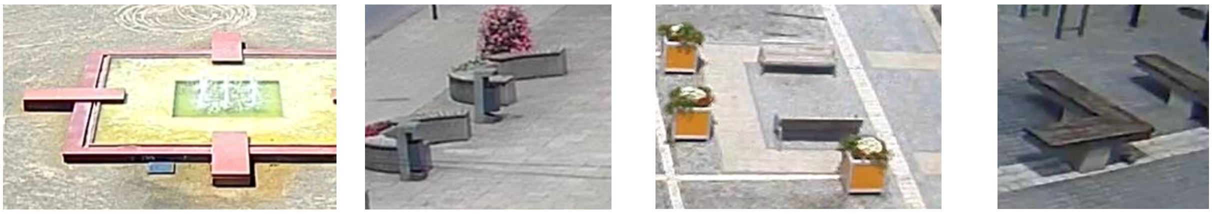
To answer the research question about the impact of street seating on the vitality of public places, this research created a complete understanding of the street seating in the observed public places. Chapter 2.3 creates an overview of the relevant place theories for the design of street seating in public places. This chapter summarizes how these findings were applied in the research and influenced the selection of street seating criteria. Based on the place theory, four attributes of furniture were considered in this research:

- The variety of street seating is relevant to give place users options to choose from influencing their social comfort (Whyte, 1980). It was observed by counting the number of different seating types per place.
- The edge effect has a great influence on the use of street furniture (Alexander, 1977; Gehl & Svarre, 2013; Main & Hannah, 2009; Whyte, 1980). Every observed seating element was classified as "edge effect" seating when the back of the user is protected by a wall, ridge or greenery. Figure 3-3 shows examples of seating that is placed next to edges from the final place dataset of this research.
- The sociality of the seating also influences the use of street seating. Socio petal seating contributes to more group activities, while socio fugal seating allows quiet use of furniture (Lesan & Gjerde, 2021; Main & Hannah, 2009). Figure 3-4 displays some examples of socio petal furniture.

- The total seating space has a significant impact on the vitality of places as observed by Whyte (1980). This research therefore calculated the seating length for each seating element.

a) b) c) d)

Figure 3-3: Examples of seating placed next to edges at four different places.



a) b) c) d)

Figure 3-4: Examples of socio petal seating at four different places.

To consider a good variety of furniture as recommended by Whyte (1980) and Main and Hannah (2009) but also by keeping a significant sample size of each furniture type, four seating types were considered: benches, chairs, ridges, and steps.

- **Bench**: Dedicated seating element with a place for multiple people. Benches can have a variety of seating surfaces and geometry. This research classified every dedicated seating with more than one place to sit as a bench.

- **Chair**: Dedicated seating for only one person. Can be moveable or fixed chairs, with or without lean or armrests. This research classified every dedicated seating with exactly one place to sit as a chair.

- **Ridge**: Secondary seating. Officially designed as a barrier between place functions or property. Literature has shown that ridges are often used for sitting (Gehl, 2013; Main & Hannah, 2009; Whyte, 1980). This research included every barrier that has a suitable height and depth but is not a dedicated seating as a ridge.

- **Step**: Secondary seating. Officially designed to overcome height differences in a space, such as elevation changes. Steps, whether individual or as part of a staircase, can also serve as informal seating. For this research, every step was considered potential seating, and staircases (composed of multiple steps) were likewise included as "steps".

While ridges and steps are no dedicated seating, researchers like William H. Whyte have highlighted the preferred use of these seating types by users and their great addition to existing primary street seatings. For each seating type, the seating length of the furniture was calculated and summarized for every place. For chairs, a seating length of 0.4 m was assumed. The selected seating metrics are summarized in Table 3-1 together with their corresponding units.

Table 3-1: Seating metrics used in this research displayed with their corresponding units.

Seating attributes	Unit
Furniture number	No.
Unique furniture types	No.
Seating length of benches	m
Seating length of chairs	m
Seating length of ridges	m
Seating length of steps	m
Total length of seating	m
How much seating is next to edges	%
How much seating is socially oriented	%

3.1.2 Place Observation

The observation times and periods followed classical research about the manual observation of public places. Based on the guideline “How to study public places” (Gehl & Svarre, 2013) and experience from Whyte (1980), Chapter 2.2 summarized relevant observational theories. From these theories, various implications for the place observation for this research were derived.

- **Duration:** For various studies, Jan Gehl used different observation times. To learn more about a place, he observed it for ten minutes each hour for multiple hours. For other research, he only observed the space for 5 minutes. This study followed a study over movement patterns across squares from which he learned, that “after only 30 minutes of observation, the dominant movement patterns were clear” (Gehl & Svarre, 2013, p. 89).
- **Timing:** Gehl suggested observing places at multiple times, days, and seasons to learn the different usage of the place. Whyte described three different “interesting” timeslots during working days: The morning is the time of commute which can tell about how people move in a place and how the place is used for necessary activities. During the time between noon and 2 pm a peak of the place-use can be expected. It is therefore a good time to compare how different places are used and how the place is used with high user densities. And finally, it is described, how places “go dead” after 6 pm. This is therefore a suitable timeslot to observe how people use the place when they have a free choice of using it. Also, Gehl highlighted the need to observe the “optional behavior” of users in a place.
- **External impacts:** There are occasions on which public places should not be observed to learn more about the use of spatial elements. Gehl especially highlighted the need for “good weather”. This was supported by Zacharias et al. (2004) in a data-driven study which revealed that weather had the biggest influence on place use. Gehl also suggested not to observe places where special events such as farmers' markets or demonstrations are happening and “normal movement patterns” are distracted by the event.

Next to the observation time of public places, other elements also impact the use of public places. Urban place research highlighted that a holistic understanding of the place and the observational conditions is needed to derive implications of public place observations. Research emphasized that many elements can change the vitality of public places (Gehl, 2013; Jacobs, 1961; Whyte, 1980; Zacharias et al., 2004). Zacharias et al. (2004) demonstrated in a quantitative study the significant impact of temperatures on place use. Whyte (1980) and Gehl (1987) observed the high impact of other spatial elements. They specifically pinpointed the effect of places like cafés or restaurants, as they not only contribute with their services but also add other amenities such as restrooms or shading to public places. Following Jane Jacobs' understanding of "Eyes on the Street" (Jacobs, 1961), restaurants can also contribute to safety in public places. Next to seating, research also highlights the importance of street furniture like fountains. Fountains are seen as a multifunctional element that can provide cooling during warm days or a playground for children, while providing a pleasing sound.

Table 3-2 summarizes the collected information about public places. It must be noted that the observed place attributes do not cover every element that impacts the use of public places. E.g. Switalski et al. (2023) highlighted the impact of the placemaking process on the meaning and therefore use of places. Carra et al. (2022) summarized how important the walkability of public places is for their use and Whyte (1980) stressed the need for a good connection between public places and transport systems. Whyte also introduced the term "triangulation" which describes the need for public space elements that attract the attention of visitors and thereby create interactions between the place users. Elements for triangulation can be (among others) monuments, art, street vendors, or musicians.

Table 3-2: Parameters that will be observed in this research with their corresponding unit.

Variable	**Comment**	**Unit**
Place area		m^2
City residents		No.
Temperature		°C
Windspeed		m/s
Humidity		%
Presence of a café		Yes/No
Presence of a Fountain		Yes/No
Recording morning	8:00-8:30	
Recording noon	12:30-13:00	
Recording evening	18:00-18:30	
Recording Saturday	12:30-13:00	

These and other elements of the urban surroundings shape how places are used. The impact of these considerations is discussed more detailed in Chapter 5.1. This research aimed to cover important factors of place use, such as the weather and spatial elements, while excluding other relevant factors due to the limited availability of data and resources. Within this scope, an extensive place database was created, incorporating spatial elements and observations recorded across four different timeslots.

3.1.3 Place Recording

Most of the available public place research relied on the physical presence of researchers in the observed place (Gehl & Svarre, 2013; Lesan & Gjerde, 2021; Shaftoe, 2012; Whyte, 1980). Even research that utilized tracking algorithms for place analysis needed to manually install cameras in the public place (Ceccarelli et al., 2023; Hou et al., 2020; Loo & Fan, 2023; Niu et al., 2022). This research utilized publicly available webcams in European cities to collect data for place observation. This allowed a scalable approach to place analysis and resulted in higher significance for the statistical analysis.

Many cities worldwide have webcams installed next to a public place. This service is often provided by tourist agencies, municipalities, or hotels. The webcam streams are available through platforms like YouTube. This research reviewed two main databases about publicly available webcams to extract

European place webcams (*Europe - Webcams*, n.d.; *Live HD Streaming Webcams from around the Globe*, n.d.). Webcams were selected based on technical and methodological criteria:

- A public place as defined in Chapter 1.4 had to be visible in the video.
- The stream had to be recordable through VLC media player.
- The stream had to have a framerate of at least 15 fps to ensure good tracking results.
- The stream had to be free of major lags or compression- and pixel errors. Humans had to be clearly visible in the video.

Based on the theoretical knowledge about observation methods for public place research, this research observed each place at four different timeslots for each 30 minutes:

- Morning: 8:00 – 8:30 local time
- Noon: 12:30 – 13:00 local time
- Evening: 18:00 – 18:30 local time
- Saturday: 12:20 – 13:00 local time

Places were not observed when it was raining or when events (e.g. markets and parades) changed the general use of the place. Figure 3-5 shows two examples of places that were not observed due to events. When necessary and possible, observations were repeated at a later point to ensure a full set of data.

a) b)

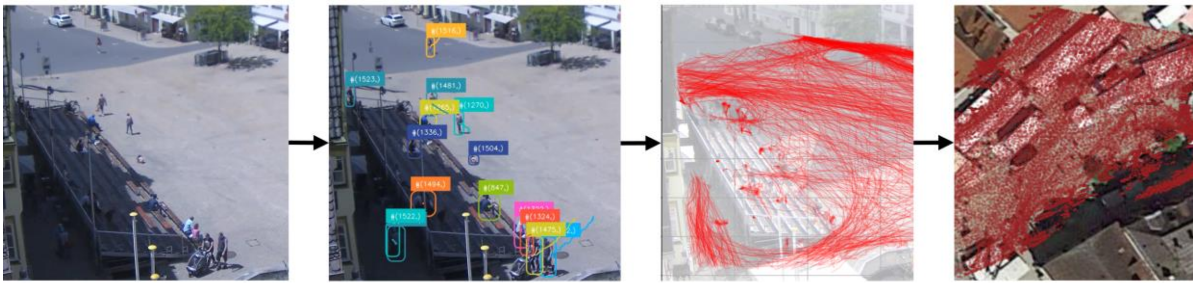
Figure 3-5: Two reasons for excluding a place from the observation: a) food market in Sittard, Netherlands; b) parade in Biberach, Germany.

Online available webcams generated streams with various resolutions, framerates, and availability. In the first step of data processing, this research uniformed the resolution of the videos to HD (1280x720pixels). The framerate was reduced to 15 frames per second to reduce the total number of frames while keeping enough information for a sufficient tracking (compare chapter 3.2.2). To ensure a uniform video length, each stream was recorded for exactly 30 minutes.

3.2 Trajectory Extraction

This research utilized a computer vision approach to quantify the impact of street seating on the place vitality. Chapter 2.2 describes how human trajectories can be used to derive information about the place vitality. It was therefore fundamental for this research to extract human trajectories from the collected video material.

The trajectory extraction from video material included three steps. Firstly, *object detection*, secondly *object tracking,* and thirdly *georeferencing*. Chapter 3.2.1 describes how object detection was used to extract the position of humans from the raw video material (see Figure 3-6-b. Chapter 3.2.2 describes the process of extracting trajectories for each human in the place (see Figure 3-6-c). Ultimately, the process of georeferencing is described in Chapter 3.2.3 to transform the trajectories from pixel coordinates into real-world coordinates (see Figure 3-6-d). Each of the steps relied on the suitable selection of algorithms for the case study and chosen indicators. By answering SRQ3, these algorithms were extracted from the literature and tested with comparable video material. This followed the objective of high accuracy of image recognition and reliability of tracking.



a) b) c) d)

Figure 3-6: The steps of trajectory extraction from a) Raw video material: b) Object detection resulting in identification of pedestrians; c) object tracking resulting in trajectories in pixel coordinates; and d) georeferencing resulting in trajectories in geo-coordinates.

3.2.1 Object Detection

Object detection is a fundamental task in computer vision that involves identifying and localizing objects within images or videos. It combines object classification with spatial localization, making it critical for a wide range of applications (Jiang et al., 2019).

Likewise other fields of application, object detection for pedestrian trajectory extraction in the field of urban data analysis comes with the need for consistent results with high precision and recall (more about detection evaluation in Table 3-4). This is important to extract the exact positioning of people in the urban place for every frame of the video (Rainio et al., 2024).

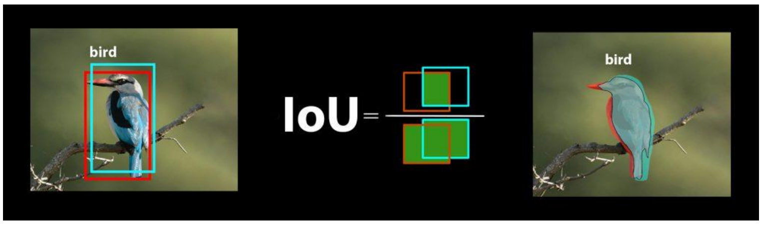
This research project came with more preconditions: Firstly, the algorithm had to process almost 80 hours of video material which set the need for efficient data processing. Secondly, the object detection algorithm needed compatibility with a tracking algorithm (see Chapter 3.2.2) and thirdly, it had to be implementable by researchers outside of computer sciences. Finally, the object detection algorithm had to be free to use for research purposes. Appendix A describes the process of the algorithm selection and provides more background information about available algorithms.

In line with similar research in the urban domain (Ceccarelli et al., 2023; Niu et al., 2022), this research utilized the object detection algorithm YOLO (You only look once). YOLO is available as an open-source Python package and implemented together with various trackers and full examples of the code. The hardware requirements were compatible with accessible hardware and time constraints (*Home - Ultralytics YOLO Docs*, 2024).

Next to the selection of a specific object detection model, datasets used for the training of object detection models have a significant impact on the model's performance (Shao et al., 2018; Zhao et al., 2018). A model mostly trained on humans can detect humans better than a model trained on various classes, such as trees, cars, animals, and humans (Girshick et al., 2014; J. Li et al., 2023). In the context of training and evaluating human detection models, mostly the COCO dataset (Lin et al., 2014) and the crowdhuman (Shao et al., 2018) dataset stand out. Both datasets are described in the Appendix A.

YOLO comes in several versions with multiple pre-trained models based on various training datasets. In this research, various combinations of versions and models were tested (J3lly-Been, 2024; Jocher, 2020; Jocher et al., 2023; A. Wang et al., 2024; Wangjianan, 2023). To evaluate the model's performance, this research measured the precision, recall, the mean average precision (mAP) for an "intersection over Union" (IoU) of 50 and 95 following Rainio et al. (2024). These evaluation metrics are summarized in Table 3-3.

Table 3-3: Metrics for machine learning evaluation based on Rainio et al. (2024).

Metric	Description
Intersection over Unit (IoU)	In object detection, the evaluation of a classification task is not as clear as in other machine-learning tasks. A bounding box around an object might surround the correct object and give the correct label but varies slightly from the "ground truth" bounding box. A pure comparison of values results in a negative evaluation. This is where the IoU creates a better evaluation metric of object detection results. By comparing the intersection of the predicted instance and the ground truth instance, an evaluation result can be labeled as correct, when the intersection is e.g. 50%. The IoU is used for the calculation of precision, recall and mAP.  *Figure 3-7: Visualization of the Intersection over Union (*Intersection Over Union IoU in Object Detection Segmentation*, n.d.).*
Precision (P)	Precision is the percentage of correctly classified instances in the set of all classified instances. It is calculated by dividing the correctly classified instances (true positive, TP) by the sum of the TP instances and the wrong classified instances (false positive, FP).
Recall (R)	Also called "sensitivity" or "true positive rate" describes the percentage of the correctly classified instances in all positively classified instances. It is calculated by dividing the number of TP instances by the sum of TP instances and false negative instances.
Mean average precision (mAP)	A model evaluation metric describing the surface below a mean precision/recall curve for every predicted class. In the case of human detection, the two involved classes are "humans" and "background". The mAP value can be calculated for different IoU threshold such as IoU=50 or IoU=95.

From the comparison of different YOLO object detection models which were pre-trained on a variety of datasets, YOLOv8m pre-trained on the crowdhuman (Wangjianan, 2023) dataset stood out as the best object detection model. Validated on the crowdhuman dataset, it achieved high scores for precision and recall even for a strict IoU of 95%. To utilize the speed of the newer version of YOLOv10 (A. Wang et al., 2024) and the accuracy of a custom-trained model, the crowdhuman (Shao et al., 2018) dataset was downloaded and adjusted to the YOLO dataset structure. YOLOv10l has been trained on it for 300 epochs. The training was computed on a NVIDIA RTX 3070 Ti with 8GB of GPU-RAM and 64GB of RAM. The process took 72 hours and resulted in significant improvements in the models' detections as highlighted in Table 3-4. Compared to the pre-trained YOLOv10l model, the precision increased by 23%, and recall increased by 38%. Compared to the pre-trained YOLOv8m_crowdhuman model, the precision decreased by 0.5% while recall increased by 3.3%. Also, mAP 50 and mAP 95 showed higher scores for the custom-trained YOLOv10l model. This is why it was ultimately chosen for the research.

Table 3-4: Evaluation results for different YOLO object detection models.

Model (pretrained)	**Source**	**Precision**	**Recall**	**mAP (50)**	**mAP (95)**
YOLOv8m	(Jocher et al., 2023)	0.671	0.437	0.513	0.273
YOLOv8m_crowdhuman	(Wangjianan, 2023)	0.876	0.661	0.725	0.509
YOLOv8_humancount	(J3lly-Been, 2024)	0.032	0.052	0.017	0.005
YOLOv8l-world	(Jocher et al., 2023)	0.624	0.471	0.530	0.278
YOLOv8x-world	(Jocher et al., 2023)	0.625	0.470	0.530	0.279
YOLOv9c	(C.-Y. Wang & Liao, 2024)	0.673	0.441	0.520	0.279
YOLOv10l	(A. Wang et al., 2024)	0.679	0.419	0.504	0.274
YOLOv10x	(A. Wang et al., 2024)	0.674	0.426	0.501	0.271
Model (custom trained)		**Precision**	**Recall**	**mAP (50)**	**mAP (95)**
YOLOv10l_crowdhuman	(custom trained)	0.871	0.684	0.787	0.528

3.2.2 Tracking

Object detection as described in Chapter 3.2.1 is a process that is repeated on every single frame of the analyzed video. The result is information about the detected class of an object and the pixel coordinates of its bounding boxes. Nevertheless, there is no continuity between the frames. This means, that a person 'A' in frame 1 that would be identified by an observer as the same person 'A' in frame 2, is only identified by two unconnected bounding boxes in frame 1 and frame 2. The computer doesn't know the relation of these two objects. To extract the trajectories of individual pedestrians, a connection of detections on consecutive frames is needed (Ciaparrone et al., 2020; Hassan et al., 2024; Luo et al., 2021). This is why tracking algorithms were deployed in this research.

Tracking algorithms generally compare detected objects in frame *n* with the objects in frame *n+1*. By assigning unique IDs to the objects, similar objects on consecutive frames can be assigned with the same ID. To reduce the complexity of the comparison of objects on each frame, tracking algorithms estimate the trajectory of each object and only compare objects in the estimated pixel space of a frame with the detected object of a previous frame. The result is continuity between frames. Person 'A' gets a random ID assigned and keeps this ID until the person is not detected anymore (Ciaparrone et al., 2020; Luo et al., 2021). Figure 3-8 visualizes the process of object tracking on the example of human detection.

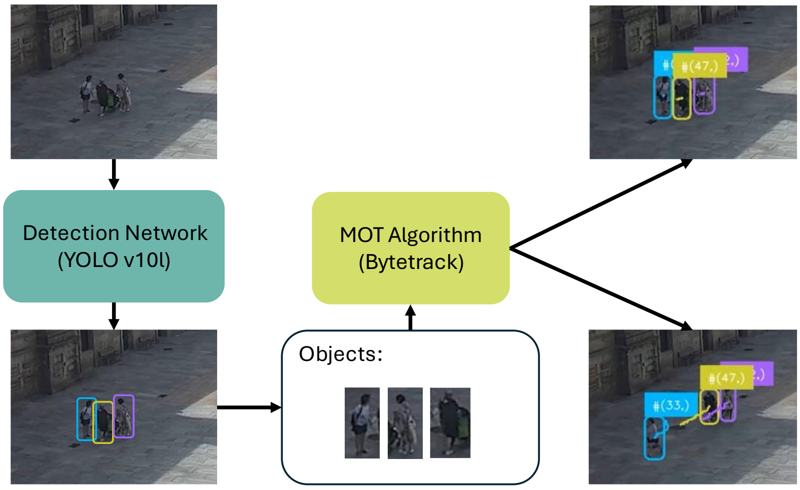


Figure 3-8: A graphic explaining the process of multi-object-tracking as adapted from Hassan et al. (2024). The objects detected by a detection network are labeled with unique IDs by the tracking algorithm.

Tracking algorithms need to mitigate various challenges in the trajectory extraction process (Chu et al., 2017; Ciaparrone et al., 2020; Luo et al., 2021; Wen et al., 2020; Zhang et al., 2021). Firstly, they need to cope with the occlusion of detected objects. For the perfect trajectory extraction, a person must keep their ID even after being occluded by an object (e.g. a tree) for a few seconds. This means the tracking algorithm must remember every detected object for a predefined number of frames (or predefined duration) and continue comparing these “buffered” IDs to objects on future frames. Secondly, tracking algorithms need to mitigate false positive detections of the object detection algorithms. An ID should not be given to a shadow that is falsely detected as a human for just one frame. And thirdly, IDs should not be swapped between objects with high similarity (“ID swap”).

Trackers are differentiated into multi-object trackers (MOT) and single-object trackers (SOT) (Hassan et al., 2024). For this research, multiple pedestrians had to be tracked at the same time which required multi-object trackers.

The MOT ByteTrack is closely integrated in the python package “ultralytics” together with the current YOLO version (*Home - Ultralytics YOLO Docs*, 2024). ByteTrack is a capable tracker and has shown in research to outperform multiple available trackers (Zhang et al., 2021). It was therefore considered to be a good option for this research. ByteTrack comes with multiple hyperparameters that needed to be tuned to mitigate the challenges of occlusion and ID swap.

Applying the tracking algorithm ByteTrack resulted in videos with annotated pedestrians which were used for debugging, hyperparameter tuning, and general understanding of the scene. Furthermore, the results of the tracking were stored in a CSV file for further calculations. This functionality was used in this research to store the extracted trajectories and, ultimately, calculate the vitality score for each place.

3.2.3 Georeferencing

As described in the previous paragraph, the location of humans (in fact: their bounding boxes) are described in pixel coordinates (A. Wang et al., 2024; Zhang et al., 2021). Pixel coordinates don't allow any implications about depth information (how far away) or information about walking speed. Due to the perspective of place webcams, humans with the same walking speed move fewer pixels in the back of the picture than in the front.

To extract information such as walking speed or user density, pixel coordinates have to be translated into real-world coordinates. In computer vision, this is usually done by creating a transformation matrix that maps the pixel coordinates into real-world coordinates. For such a matrix, multiple pieces of information about the camera are needed, such as lens distortion, the height of the camera, and its rotation in each direction. (Hartley & Zisserman, 2004). In this research, this information was unknown as the video material was collected from online available place webcams. Therefore, an estimation of the transformation matrix had to be found. This research followed the methodology "homography" used in similar research by Loo & Fan (2023). Homography suggests that two images of the same plane (in our case: the place) contain the same information just differently transformed (Zhangy et al., 1996). If multiple features can be identified in both planes, a transformation matrix (also named homography matrix) can be calculated. The homography process is less precise than working with a hardware-based transformation matrix, but the estimation of the location of humans has been proven to be precise enough for place analysis (Loo & Fan, 2023).

In this research two images of each place were available: The image of the camera and satellite imagery from Google. Google satellite imagery is visualized in the Pseudo-Mercator projection (EPSG:3857). Using homography, the coordinates of the original image from the camera were therefore transformed into the ESPG:3857 coordinates of the satellite imagery. From this coordinate system, a transformation in any other world-coordinate system is possible. Features on place imagery could be any fixed object that was visible in both images, such as street furniture, corners of buildings, pavement, stairs, or trees. Figure 3-9 shows a selection of place features that were identified in pixel and real-world coordinates for the example of Wolsztyn in Poland. When features were not visible due to bad image quality, an educated guess of feature points was made. This is generally possible because humans have been trained their whole lives to estimate depth which makes this process sufficiently precise (Ahsan et al., 2022).

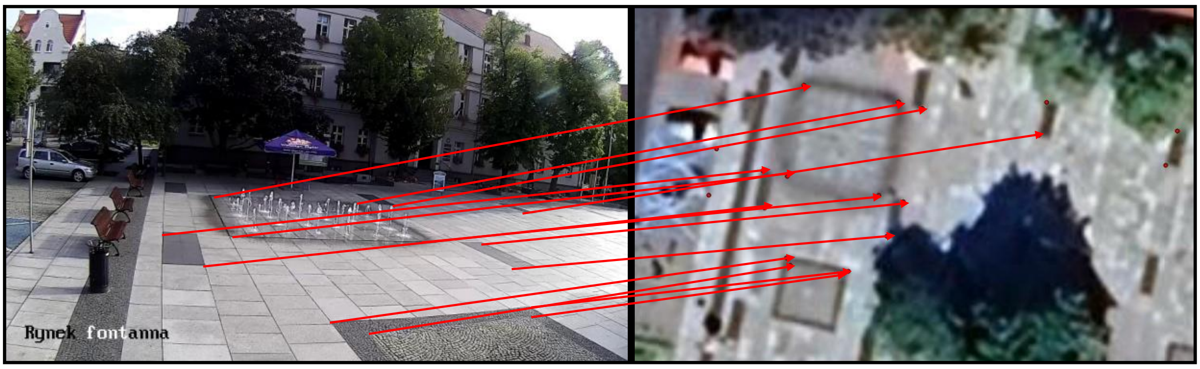


Figure 3-9: The mapping of pixel coordinates (left) to real-world coordinates (right).

For the selection of corresponding feature pairs, the "Georeferencer" of the open-source geo-information software QGIS (QGIS Association, 2024) was used which stores the location of each selected feature in pixel and geo-coordinates. A Python script based on the package OpenCV (Bradski, 2000) was used to calculate the homography matrix from the extracted feature points (*OpenCV: Basic*

Concepts of the Homography Explained with Code, n.d.). The homography matrix was finally applied to transform every pixel coordinate into geo-coordinates. The homography matrix had to be created for every place individually.

3.2.4 Data Processing

The output of object detection, tracking and geo-referencing were the pixel- and real-world coordinates for every frame and human in the observed public place. To reduce the complexity of the vitality score calculation (see Chapter 3.3) and to remove noise, multiple steps of data preprocessing were performed.

- Trajectories with less than 30 data points were removed.
- To reduce the impact of outliers of the object detection process, trajectories were smoothed by applying a moving average with a window size of 8.
- Real-world coordinates were transformed from the Mercator projection (ESPG:3857) to the coordinate system ESPG:4326 to increase the accuracy of distance and speed calculations.
- The speed was calculated for every data point for every individual pedestrian.
- The number of people was counted for each frame.

Table 3-5 summarizes the resulting variables. The complete process of data processing is described in Appendix D. The output of the trajectory extraction was one CSV file per place. Each file contained the extracted variables for every detected individual and each frame of the video. This provided the basis for the calculation of the vitality score in the following chapter.

Table 3-5: The output variables of object detection and tracking.

Variable name	Description
x_min	the left edge of the bounding box in pixel coordinates
x_max	the right edge of the bounding box in pixel coordinates
y_min	the top edge of the bounding box in pixel coordinates
y_max	the bottom edge of the bounding box in pixel coordinates
centre_x	(x_max + x_min)/2
centre y	y_max
centre_x_sw	sliding window over centre_x (window_size = 8)
centre_y_sw	sliding window over centre_y (window_size = 8)
real_world_x	centre_x transformed into ESPG:3857
real_world_y	centre_y transformed into ESPG:3857
real_world_sw_x	sliding window over real_world_x (window_size = 8)
real_world_sw_y	sliding window over real_world_y (window_size = 8)
longitude	real_world_sw_x in ESPG:4326
latitude	real_world_sw_x in ESPG:4326
class_id	The ID of a class follows the definitions of the COCO dataset. In this research always '0' for the class human
confidence	percentage of confidence that the bounding box describes the specific class
tracker_id	a unique ID for every detected human
frame_index	The video frame on which the detection was performed. For a video with 15 frames per second (fps), there is a time difference of 0.067 seconds between every frame.
speed	in m/s calculated based on longitude and latitude
nr_people	number of unique tracker_ids calculated for each frame

3.3 Place Vitality Assessment:

Chapter 2.2 summarizes possible vitality assessment methods for public places. The methods differ between: i) manual and automated; ii) place scale and city scale; and iii) how they are built upon place theory. This research was applied on the place scale for various public places in Europe, relying on automated methods developed for the place scale. This is why this research followed the vitality score developed by Niu et al. (2022).

Niu et al. developed a vitality analysis based on human trajectories. Building upon Gehl & Svarre (2013), they proposed the indicators "number of people", "duration of stay", "trajectory diversity", and the "trajectory complexity" for a vitality scoring. Trajectory diversity is a proxy measure for the diversity of activities in a place. Places with a higher diversity of activities are seen to be more vital. Trajectory complexity assumes that places with more complex trajectories are used not only for the needed activities (such as commuting) but also for leisure time and other "optional" activities. Trajectories are therefore more complex when people change speed and directions in a place. From the four sub-indicators for place vitality, a model for place vitality was created. By correlating the model's prediction with the prediction of an expert commission, Niu et al. validated the goodness of fit with 79%. A good percentage of the included place vitalities was therefore completely described by the statistical model.

Following the research of Niu et al. this research assessed four vitality metrics: i) the number of people (Chapter 3.3.1); ii) trajectory complexity (Chapter 3.3.2); iii) trajectory diversity (Chapter 3.3.3); and iv) the duration of stay (Chapter 3.3.4). Divergence from the original methodology of Niu et al. is described in each subchapter.

3.3.1 Number of People

The number of people is the count of unique IDs as a result of the object tracking. The calculation was done after preprocessing the data as described in Chapter 3.2.4. This indicator was calculated as in the original research by Niu et al.

3.3.2 Trajectory Complexity

To distinguish between the trajectories of place users with necessary behavior, optional behavior, and social behavior, Niu et al. used the "minimum description length" theory (MDL). The idea of MDL is to describe data (in this case trajectories) with fewer data points than originally observed. Figure 3-10 shows a complex trajectory that needs multiple data points to be described sufficiently. The original, blue trajectory can be described without much loss of information through fewer points, as visualized by the red trajectory. These relevant points are called "inflection points" and can describe a given trajectory with the least number of data points. Niu et al. simplified the trajectories utilizing the MDL and calculated based on this the complexity of each trajectory. The complexity is the length- and angle difference of all consecutive data points of each trajectory. The difference was summed for the whole place and divided by the number of trajectories. Trajectory complexity is therefore the average angle- and length differences of trajectory elements in a place. This research followed the methodology for the calculation of the trajectory complexity without changes compared to the original research of Niu et al.

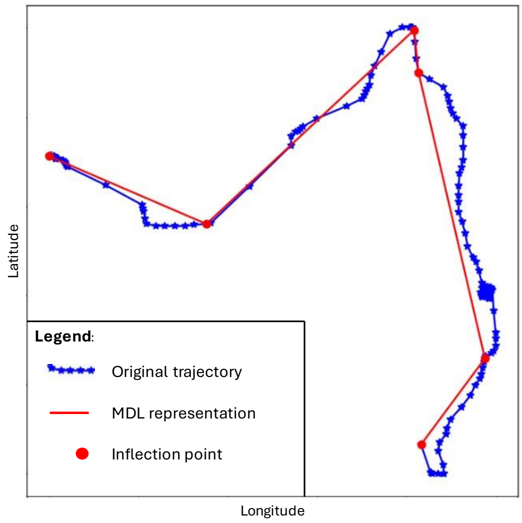


Figure 3-10: The original trajectory (Blue) can be represented with much less datapoints by creating an MDL representation (red).

3.3.3 Trajectory Diversity

To analyze the diversity of trajectories, Niu et al. developed a multistep process for trajectory clustering. The process is visualized in Figure 3-11. In the first step, the trajectories were clustered using the “Fréchet distance” (similarity of curves (Eiter & Mannila, 1994)) and hierarchical clustering into spatiotemporal clusters. These spatio-temporal clusters describe groups of people, as they are the closest in time and space. In the second step, groups that had a similar movement pattern but were spatially or timewise located differently were clustered by calculating the “structure difference” and by hierarchically clustering the groups. The result were multiple clusters each containing trajectories with similar movement patterns. To derive a diversity measure of these clusters, Niu et al. utilized the Shannon entropy (Shannon, 1948). Entropy, also known as “level of disorder,” returns a higher value for places with diverse trajectories and a lower value for places with less diverse trajectories.

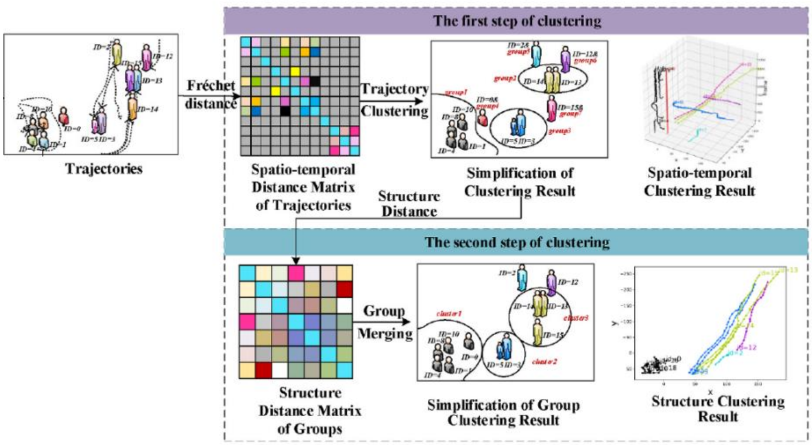


Figure 3-11: The Fréchet distance is used to identify groups of pedestrians, the structural difference is used to identify clusters of space use patterns for the calculation of the trajectory diversity (Niu et al., 2022).

The first clustering step of Niu et al. could not have been reproduced. While clustering of groups in time and space was applicable for a 1-minute video in the original research, the group detection is not possible in a 30-minute video due to a possibly much bigger distance in the time dimension. Furthermore, the clustering of groups was not reproduced due to missing hyperparameters. This research aimed to stay as close to the original approach by using the structural difference of trajectories and hierarchical clustering to identify clusters of movement patterns. For the hierarchical clustering the silhouette coefficient (Rousseeuw, 1987) was used to determine the optimal number of "good" clusters. A good cluster is seen as a cluster with elements of high similarity within the cluster but a clear separation from elements outside of the cluster. Based on the distribution of trajectories in the clusters, the Shannon entropy was calculated similarly to Niu et al.

3.3.4 Duration of Stay

Niu et al. included two conditions to identify staying people: Trajectory clustering was used to identify point clouds in the location data of single trajectories. A trajectory that contained such a cluster of points was identified as staying. The second condition was a stay point detection based on the MDL representation as described in Chapter 3.3.2. Trajectories that had more than three inflection points in the MDL representation were also identified as staying people. The duration of stay is the time difference between the first and the last appearance of a staying human in a place. These stay times were summed up for each place and divided by the number of trajectories.

The stay point detection using a clustering algorithm couldn't be reproduced due to missing hyperparameters from the original research. Also, the stay point detection using MDL was not successful as almost every trajectory fulfilled the condition of more than three inflection points. Staying people were instead defined by people that reduced their speed to a maximum of 0.2m/s for at least 5 consecutive seconds during their stay in the place.

3.3.5 Vitality Model

As a result of their research, Niu et al. created a weighted linear regression model (see Equation 3-1). Every indicator was z-normalized by subtracting the total mean from each indicator and dividing by its standard deviation. This assured comparability of places and resulted in the following equation:

$$vitality = 0.582num + 0.254dur + 0.307TD + 0.159TC \quad (3\text{-}1)$$

where num is the number of people, dur is the duration of stay, TD is the trajectory diversity, and TC is the trajectory complexity. This research utilized the methodology of Niu et al. almost unchanged. The good fit of the original model to the prediction of an expert commission and the use case of small urban places promised a suitable application of a vitality score.

3.4 Correlation Analysis

The output of the previous methodology chapters can be clustered into three categories: Place data, seating data, and vitality scores. Figure 3-12 provides an overview of seating and place attributes and the vitality indicators being part of this research. To answer the research question about the impact of street seating on the vitality of public places, the seating attributes were correlated to the vitality scores. By considering different place attributes and circumstances of the observation (e.g. weather), the correlation analysis aimed to control for place-specific factors.

Correlation Analysis

Dependent variables

- Unique seating types
- Percentage next to edge
- Percentage sociopetal
- Number of seatings
- Seating length per type

Independent variable

- Place vitality
  - Number of people
  - Duration of stay
  - Trajectory diversity
  - Trajectory complexity

Control attributes

- Observation time
- Temperature [°C]
- Place size [m^2]
- Café present
- Fountain present

Figure 3-12: Overview of the elements of the correlation analysis in this research summarizing dependent variables, the independent variable and its sub scores, and the control attributes.

The correlation analysis of street seating configurations to the vitality of places was structured into two methodologies. First, a linear correlation analysis was done to see if any correlations could be identified visually. Then, a multiple linear regression analysis was done to determine if there were any quantifiable correlations. This aimed to explore the significance of correlations between each furniture attribute and the place vitality.

As summarized in Chapter 2.2, street seating is only one of many factors that can influence the vitality of public spaces. Other elements, such as: i) temperature (Arens & Bosselmann, 1989; Zacharias et al., 2004); ii) the presence of spatial features like cafés and fountains; and iii) temporal factors have shown in the literature to significantly affect place vitality (Gehl, 2013; Shaftoe, 2012; Whyte, 1980). To better understand the specific impact of street seating on place vitality, this research accounted for these additional factors by controlling for them (Tranmer et al., 2020).

Controlling for a variable means adjusting the analysis so that the influence of a specific variable is held constant, allowing a clearer assessment of how street seating alone contributes to place vitality. In this case, the dataset was divided into subsets where the control variables, such as weather conditions or observation time, were similar across observations. This allowed this research to compare places under similar external conditions, ensuring that any observed effect on vitality could be more confidently attributed to street seating.

This research used four regression models, each examining the relationship between street seating and place vitality while controlling for different variables:

- **Variation of time**: The impact of street seating on place vitality was assessed at different times of the day (morning, noon, evening) and across different days (workdays and Saturdays). By repeating the correlation and regression analysis for each observation time, this approach controlled for time-specific fluctuations in vitality.
- **Variation of temperature**: Literature highlights the impact of the weather on place use (Arens & Bosselmann, 1989; Zacharias et al., 2004). The relationship between street seating and vitality was therefore explored while controlling for temperature, categorized into three ranges (low, medium, high).
- **Variation of place size:** The number of people in a place and their duration of stay is closely related to the size of a place. To account for this possible influence, the analysis also controlled for the size of the public space (small, medium, large).
- **Variation of spatial features:** Features such as cafés or fountains were identified in the literature to influence the vitality of places (Gehl, 2013; Shaftoe, 2012; Whyte, 1980). This research therefore also controlled the analysis for the presence or absence of fountains and cafés.

By controlling these factors, the analysis provided a clearer picture of how street seating contributes to place vitality, aiming to reduce the impact of other influential variables on the correlation and regression analysis. The results of the regression analysis were analyzed by statistical indicators as summarized in Table 3-6.

Table 3-6: statistical indicators for regression evaluation (Tranmer et al., 2020).

Indicator	Description
coefficient (Beta-value)	Represents the magnitude and direction of the relationship between an independent variable and the dependent variable while holding all other values constant.
error of standard deviation	Estimates the variability of the coefficient across different samples. Provides a measure for precision. Smaller errors indicate more precise estimates.
t-value	Measures the number of standard deviations that the coefficient is away from zero. A higher t-value indicates that the corresponding independent variable is statistically significant.
p-value	Assesses the statistical significance of each coefficient. A p-value lower than 0.05 implies that the variable has a significant impact on the dependent variable.
variance inflation factor (VIF)	Quantifies the extent of multicollinearity in the regression model. A VIF above 10 is considered to indicate a high multicollinearity which could lead to a lower reliability of the coefficient estimates.
adjusted R^2	Indicates the proportion of variance in the dependent variable that is explained by the independent variables. The adjusted R^2 adjusts for the number of predictors included in the model.

4 Results

Data about street seating, place attributes, and the place vitality of 39 European places was collected throughout the methodology of this research. This allowed a correlation analysis between multiple street seating features such as the length of benches per place or the compliance to the edge effect and the vitality of the place. Chapter 4.1.1 answers SRQ1 and summarizes the collected data to provide domain knowledge and a better understanding of the distribution of street seating. Chapter 4.1.2 answers SRQ2 and summarizes the observed places and their attributes. SRQ3 is answered in Chapter 4.2. Chapter 4.3 answers SRQ4 including a validation of the vitality score and its sub-indicators. Chapter 4.4 delves into the correlation analysis to ultimately answer the research question of this document.

4.1 Data Collection

This research collected 149 place observations spread over 39 places and four time slots through publicly available webcams. Places were observed in 10 different European countries with a high density of observations in Poland and the Czech Republic. Following the methodological framework of this research, various place attributes and seating configurations were collected as summarized in Chapter 3.1. Chapter 4.1.2 provides an overview of observed street seating elements. Chapter 4.1.1 summarizes the observed place attributes and their distribution in the dataset.

4.1.1 Seating Data

Derived from Chapter 3.1.1, four categories of street seating were collected: Benches, chairs, ridges, and steps. Figure 4-1 shows the distribution of the total length of these seating elements in the observed public places. Seven of the observed places didn't have a designated type of seating, of which three places didn't have any options to sit. On average, each place had two options of seating types and a total seating length of 40 meters. The most common seating type was a bench. Only one place offered fixed chairs. No place offered moveable chairs.

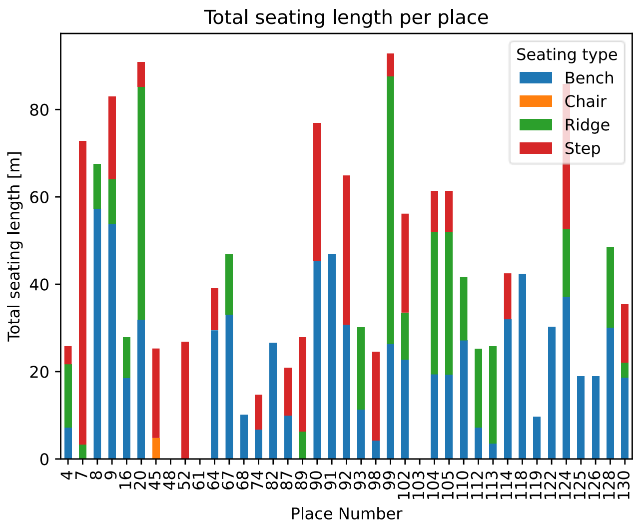


Figure 4-1: The seating length per place. Place numbers are defined in Appendix E.

Chapter 2.3 highlights the importance of choice and the importance of the edge effect on the acceptance of street seating. Therefore, each seating element was categorized into its compliance to the edge effect. Of 304 classified seating elements in the observed places, 38% of the seating was arranged next to edges. Figure 4-2 displays, that most of the places didn't have any seating next to edges. In only 15 of the observed locations, more than 50% of the seating was positioned along the edges.

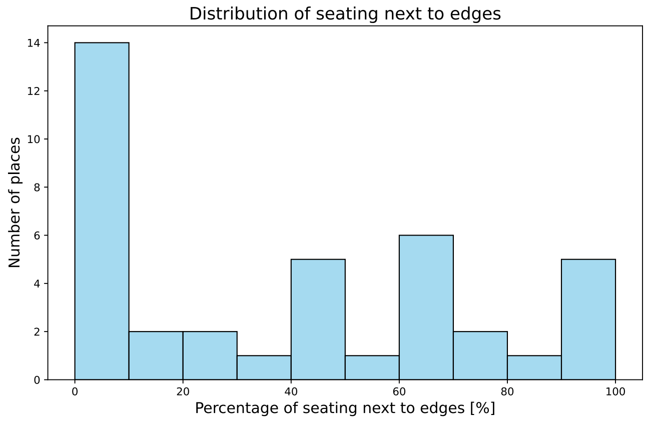


Figure 4-2: Distribution of street seating placed next to edges per place.

Derived from Lesan & Gjerde (2021), this research also assessed the sociality of street seating. Socio petal configurations were identified for 17% of the seating. Figure 4-3 shows that most of the places didn't have any socio petal seating configurations.

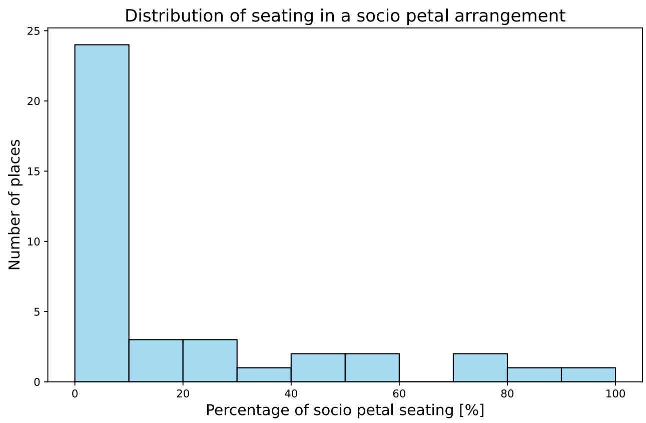


Figure 4-3: Distribution of socio petal seating configurations per place.

4.1.2 Place Data

A first selection process of place webcams based on the methodology of this research resulted in a list of 130 publicly available webcams that were streaming public place videos. By testing the streams and the visibility of humans for the object detection algorithm, the place selection was reduced to 39. These places are public places in Europe. Appendix E lists every observed place including its location and recording details.

The average size of the observed places is 2,170m². The observed places were mostly found in cities with less than 5,000 residents while some of the cities had more than 300,000 inhabitants. Places in Poland accounted for almost half of the observed places. Places were observed in 10 different countries as shown in Figure 4-4. Cafés were observed in 62.5% of the places, fountains were observed on 42.5% of the places.

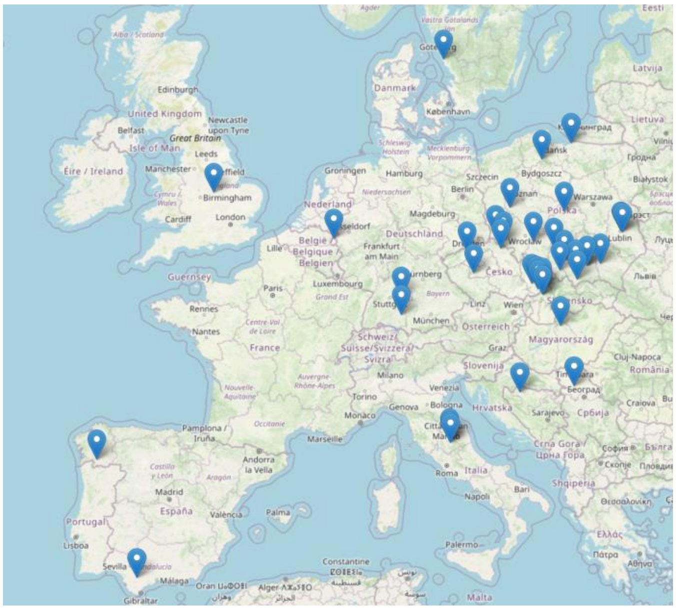
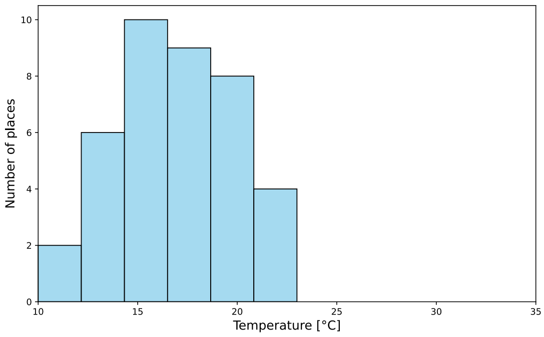
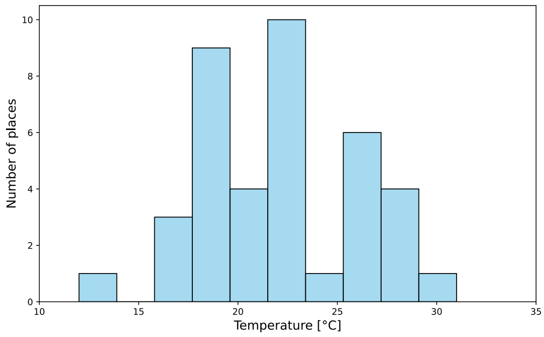


Figure 4-4: Locations of observed places in Europe.

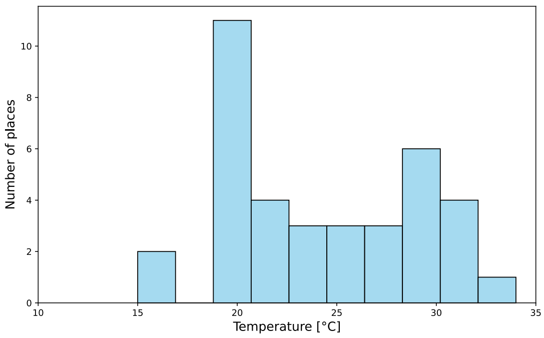
The weather during each observation was dry. Due to a heat wave in eastern Europe in June 2024, observations in Poland and the Czech Republic showed temperatures of more than 25°C. Especially observations during the evening and on Saturday were made during high temperatures (See Figure 4-5).



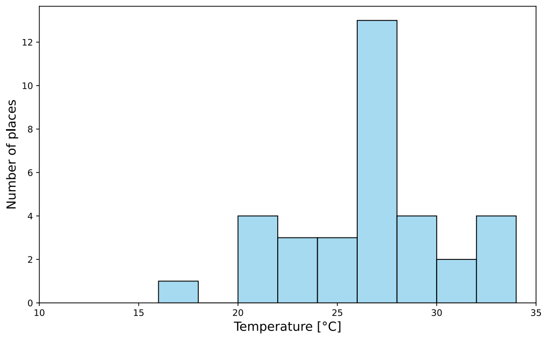
a) Morning



b) Noon



c) Evening



d) Saturday

Figure 4-5: Distribution of the temperature during morning (a), noon time (b), evening (c), and on Saturday (d).

4.2 Trajectory Extraction

The trajectory extraction in this research was divided into three subthemes: Object detection, object tracking, and georeferencing. By applying these three steps, this research extracted human trajectories in real-world coordinates from webcam videos. This chapter outlines the results of the trajectory extraction process by also indicating the limitations of the process.

4.2.1 Object Detection

Following the requirements as outlined in Chapter 3.2, this research utilized the object detection algorithm YOLOv10l which was custom trained on the crowdhuman dataset to improve human detection. Next to others, two metrics for the evaluation have been introduced: Precision and Recall. Precision measures the accuracy of a model in positively predicting instances (here: humans). Recall measures the model's ability to identify all relevant instances. To evaluate the precision and recall of the applied object detection algorithm on the data of this research, 50 random frames from the total video dataset were extracted to manually evaluate the positive and negative detections as well as the false positive and false negative detections.

Over all instances (humans) of the sample data, object detection achieved a precision of 93.8% (Figure 4-6) and a recall of 92.8% (See Figure 4-7). The average precision of all place samples is 88.3%, and the average recall is 83.5%.

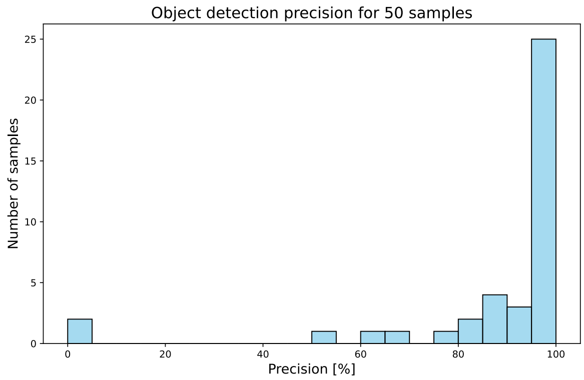


Figure 4-6: Precision of YOLOv10l for a sample of n=50 frames.

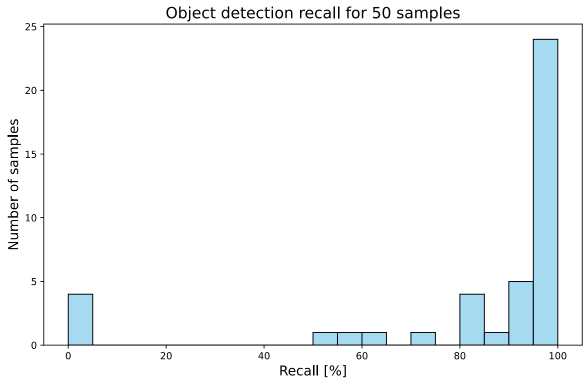


Figure 4-7: Recall of YOLOv10l for a sample of n=50 frames.

Analyzing evaluated samples with a precision and recall of 0% revealed that these places were not visited at that time but place furniture like human shaped statues were falsely classified as humans. Places with more observations resulted in very good precision and recall and therefore good object detection results.

4.2.2 Tracking

By giving detected humans a unique ID, and tracking these humans over consecutive images, tracking algorithms can create trajectories of humans. Due to the integrated compatibility of the object tracker "ByteTrack" with YOLO object detection, and its reliable results in the literature, this research used this multi-object tracker for trajectory extraction.

The manual labeling of multiple video sequences and human IDs for an algorithmic evaluation of the tracking results was not possible in the time frame of this research. Instead, the tracking results were evaluated visually. By overlaying trajectories with the original video file, a qualitative assessment of the tracking was performed.

This qualitative assessment allowed the optimization of the hyperparameters of ByteTrack. The best tracking results were achieved with the following parameters:

- *track_activation_threshold* = 0.30: A trajectory was only created for humans that were detected with a confidence of at least 30%.
- *lost_track_buffer* = 125: If a human disappeared on a frame due to occlusion or misdetection, ByteTrack stored their ID for 125 frames waiting for them to reappear.
- *minimum_matching_threshold* = 0.95: The similarity between humans on consecutive frames had to be at least 95%.
- *minimum_consecutive_frames* = 3: A trajectory was only created when a human is detected for more than 3 consecutive frames.

Common challenges for tracking algorithms are crowded scenarios and the occlusion of place visitors. Also in this research, swapped IDs between humans with crossing trajectories and lost IDs of occluded humans (e.g. by a truck as visualized in Figure 4-8) were observed.

Figure 4-8: Occlusion due to a parked truck results in suddenly ending trajectories.

However, humans with low walking speeds or sitting humans were usually not affected by ID swaps or occlusion. Also, the trajectory complexity and diversity were not influenced as even a reassigned "complex" trajectory resulted in the same trajectory complexity. Only the number of people can be potentially higher in places with many occlusions and therefore reassigned IDs. An inspection of the final vitality score did not indicate a significant impact of occlusions on the place's vitality score.

4.2.3 Georeferencing

This research utilized a homography matrix to transform pixel coordinates from observation videos into real-world coordinates. An average of 20 features were selected per place in pixel and in real-world coordinates to create a complete homography matrix and therefore good georeferencing results. A visual inspection of the resulting trajectories was done by comparing trajectories and their relation to specific landmarks (e.g. street furniture or pavement patterns) in pixel coordinates to the same landmarks in real-world coordinates (One example given in Figure 4-9). By plotting every trajectory dataset over a place image, artifacts or mismatches were identified and corrected by optimizing the homography matrix.

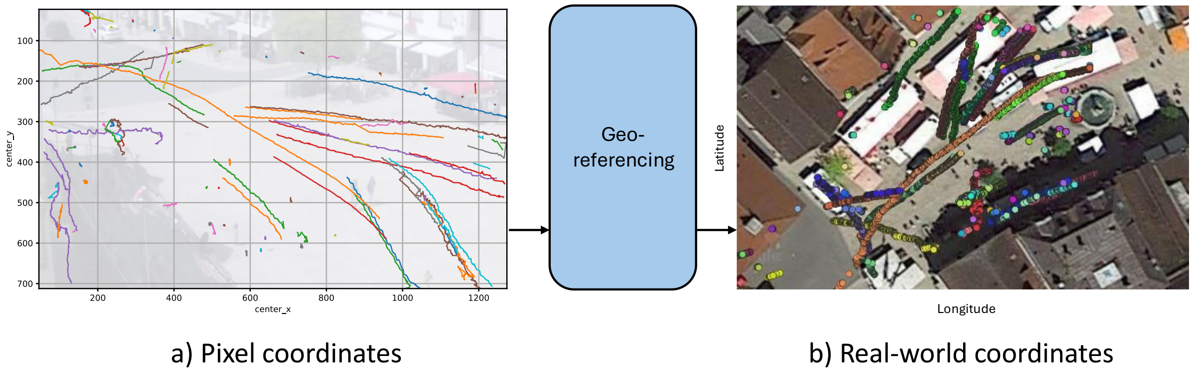


Figure 4-9: Process of georeferencing: a) trajectories in pixel coordinates, b) the same trajectories in real-world coordinates.

By applying object detection, tracking, and georeferencing on the collected webcam videos of this research, a complete trajectory dataset in real-world coordinates was created. Each step showed good results, and the trajectories therefore could be used for the trajectory-based vitality score calculation of this research.

4.3 Place Vitality Assessment

The vitality score of the public places of this research consists out of four sub-indicators as described in Chapter 3.3: the number of people, the duration of stay, the trajectory diversity, and the trajectory complexity. Therefore, the vitality of a place scores high when many people are present, but also when the people present performed a variety of activities or stayed for a long time. The vitality scores were z-normalized to allow a comparability of different places.

Figure 4-10 shows, using the example of the “plaza major” in Celanova (Italy), that the vitality score and its sub-indicators returned plausible results. The vitality score follows the density and complexity of visible trajectories. Furthermore, a higher duration of stay is recognizable where there are more stay points in the trajectory plot (Figure 4-10, Saturday).

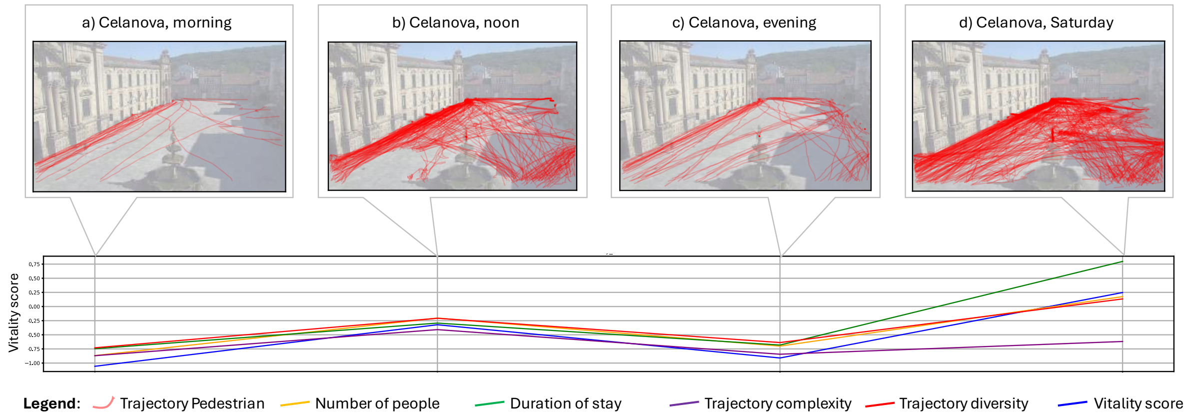


Figure 4-10: The variation in place vitality over time in Celanova, Italy. A low vitality score was observed in the morning (a) and in the evening (c). At noon (b), the vitality score was lower compared to Saturday (d), where the score was higher, largely due to longer durations of stay.

Due to the z-normalization of the vitality score, the mean over all observations is equal to zero. The three places with the highest vitality score are displayed in Figure 3-11 (top). Nove-Sad had the highest vitality score of 7.2. The vitality score of Szersk and Assisi were measured with 3.9 and 3.5 respectively. The observation in Novi-Sad is therefore a positive outlier in this dataset. The three places with the lowest vitality score are displayed in Figure 3-11 (bottom). Each place was barely visited during the observation resulting in vitality scores of -1.1 for Kromeriz, Bevagna, and Celanova. The resulting vitality scores and their ranking were therefore plausible and the methodology by Niu et al. (2022) successfully applied to this research.

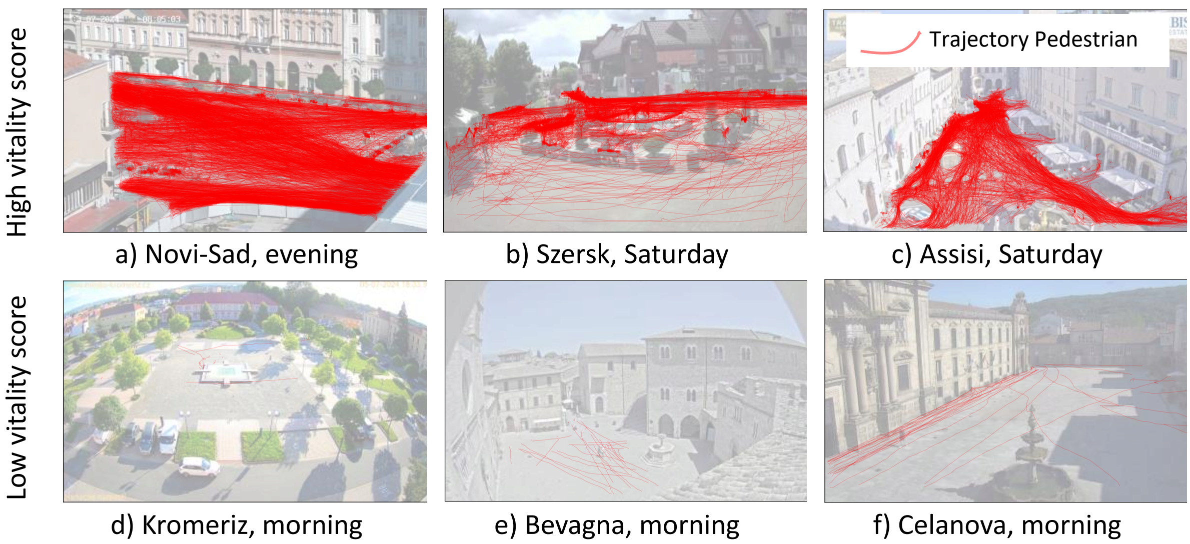


Figure 4-11: Visualization of places with the highest vitality score in a), b), and c). Visualization of places with the lowest vitality score in d), e), and f).

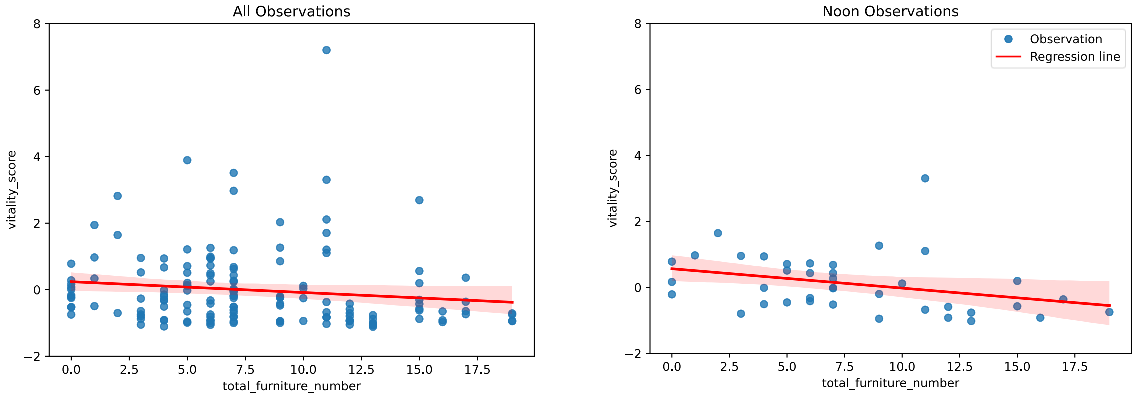
4.4 Correlation Analysis

This research explored the impact of street seating on the place vitality by correlating street seating features to the vitality of the observed places. Explored street seating features were the variety and total number of seatings, the length of different seating types, and the compliance to the edge effect and socio petal arrangement of the seating.

To account for the impact of other factors, such as weather or spatial elements of the place on the place's vitality, the correlation analysis was controlled by: i) observation times (Chapter 4.4.1); ii) temperature ranges (Chapter 4.4.2); iii) place sizes (Chapter 4.4.3); and iv) the presence of cafés and fountains (Chapter 4.4.4). The statistical analysis of the impact of street seating on the place vitality was performed in two steps per model: visual inspection of the correlation in correlation plots and a multiple linear regression analysis to identify the significance of and collinearity between the independent variables.

4.4.1 Analysis Controlled by Observation Time

Correlating the vitality score for every observation to the furniture attributes revealed no clear results. Only the total number of furniture seemed to have a slight negative impact on the place vitality. Controlling the analysis by the observation time increased this correlation for the observations during noon time (See Figure 4-12). Neither the multiple linear regression model for all observations (R^2 = 0.076) nor for the noon observations (R^2=0.106) was statistically significant. No statistically significant correlations were found for the observations during morning, evening and Saturday. The models suggest that there is no significant impact of street seating on the place vitality.

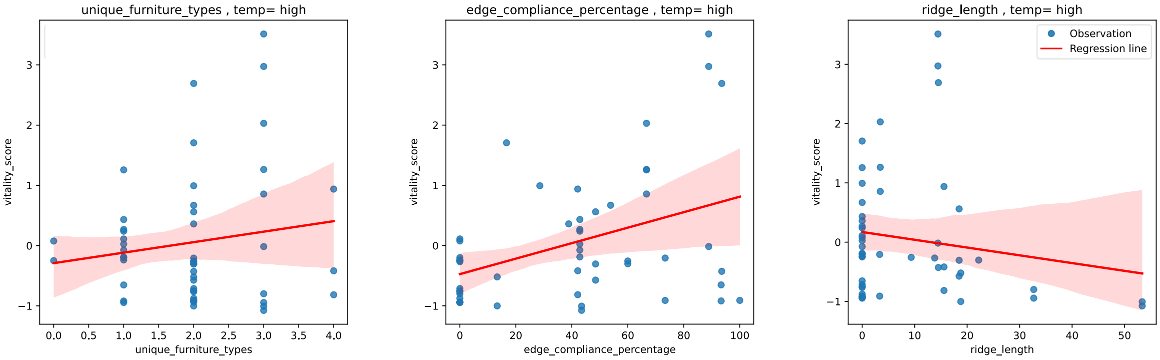


a) b)

Figure 4-12: A weak negative correlation between the total number of furniture and the vitality score could be observed for all observations (a) which became stronger by controlling for the observation time (b).

4.4.2 Analysis Controlled by the Temperature

To account for the impact of temperature on the place vitality, three temperature ranges were explored: i) temperatures lower than 15°C; ii) temperatures between 15°C and 25°C; and iii) temperatures above 25°C. For temperatures below 15°C only nine observations were made. As this does not appear significant, the model was not further investigated. No significant correlation was found for the model with temperatures between 15°C and 25°C. The model for high temperatures had the best fit with an R^2 of 0.34. The multiple linear regression revealed a relevant positive impact by the count of unique furniture types (coefficient=0.6) and a weak negative correlation for the seating length of steps and ridges. Also, the edge effect had a low positive coefficient of 0.1 (See Figure 4-13). This indicated (within the low significance) that places with a variety of furniture types and with seating placed next to edges while having shorter ridges and steps tend to have higher vitality scores.



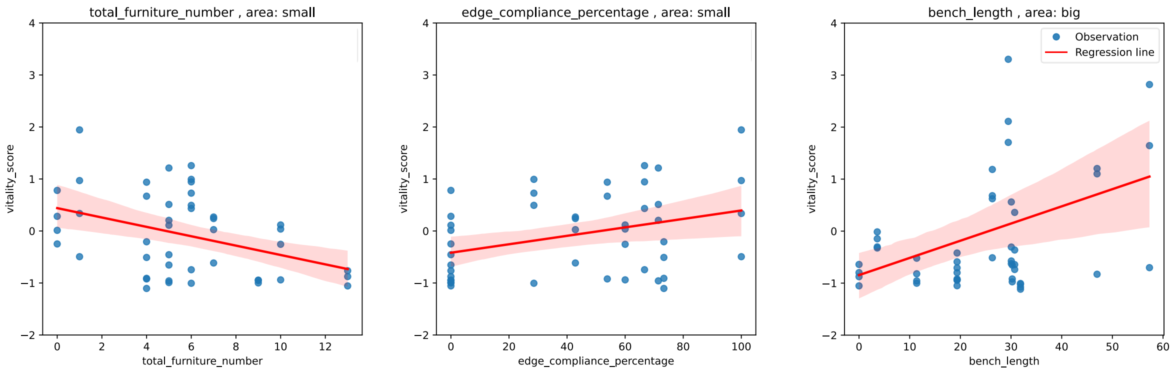
a) b) c)

Figure 4-13: Correlation between the number of unique furniture types (a), compliance to the edge effect (b), and the ridge length (c) for temperatures above 25°C.

4.4.3 Analysis Controlled by the Place Size

Whyte (1980) suggested that the place size has no impact on the number of people. However, the sub indicators "number of people" and the "duration of stay" are directly linked to the size of a place. This research therefore controlled the analysis also by the place size. The category "small places" summarized any place with less than 1,500m². Places with a size between 1,500m² and 2,500m² were summarized in the category "mid" and places larger than 2,500m² were summarized in the category "large". The size ranges were based on the distribution of places.

Controlling the analysis by the place size revealed some correlations that were not seen in the analysis before. For small places, a negative correlation for the number of furniture was observed (See Figure 4-14-a). Also, the positive correlation for the edge effect seemed to be stronger than for other subsets of observations (See Figure 4-14-b). For big places, a positive correlation between the bench length and the vitality was observed (See Figure 4-14-c). Nevertheless, these observations were inconclusive for the different place sizes. While e.g. the edge effect had a positive coefficient for small places, it had a negative coefficient for big places. It should be noted that while these are interesting findings, the correlations are not clear enough to derive implications about furniture use in differently scaled places.



a) b) c)

Figure 4-14: A negative correlation can be seen between the place vitality and total number of furniture (a), while a positive correlation is visible between the vitality and the compliance to the edge effect (b) and the compliance to the total bench length (c).

4.4.4 Analysis Controlled by Place Attributes

This research controlled the correlation analysis also by the presence and absence of cafés and fountains. Places with either a café or a fountain showed generally stronger correlation between the seating attributes and the place vitality (see Figure 4-15). It therefore seemed to be relevant for the impact of street furniture attributes on the place vitality what other features were present in the place. Nevertheless, the exact influence of place features on the impact of street seating on the place vitality was inconclusive as both models were statistically insignificant with an R^2 below 0.2.

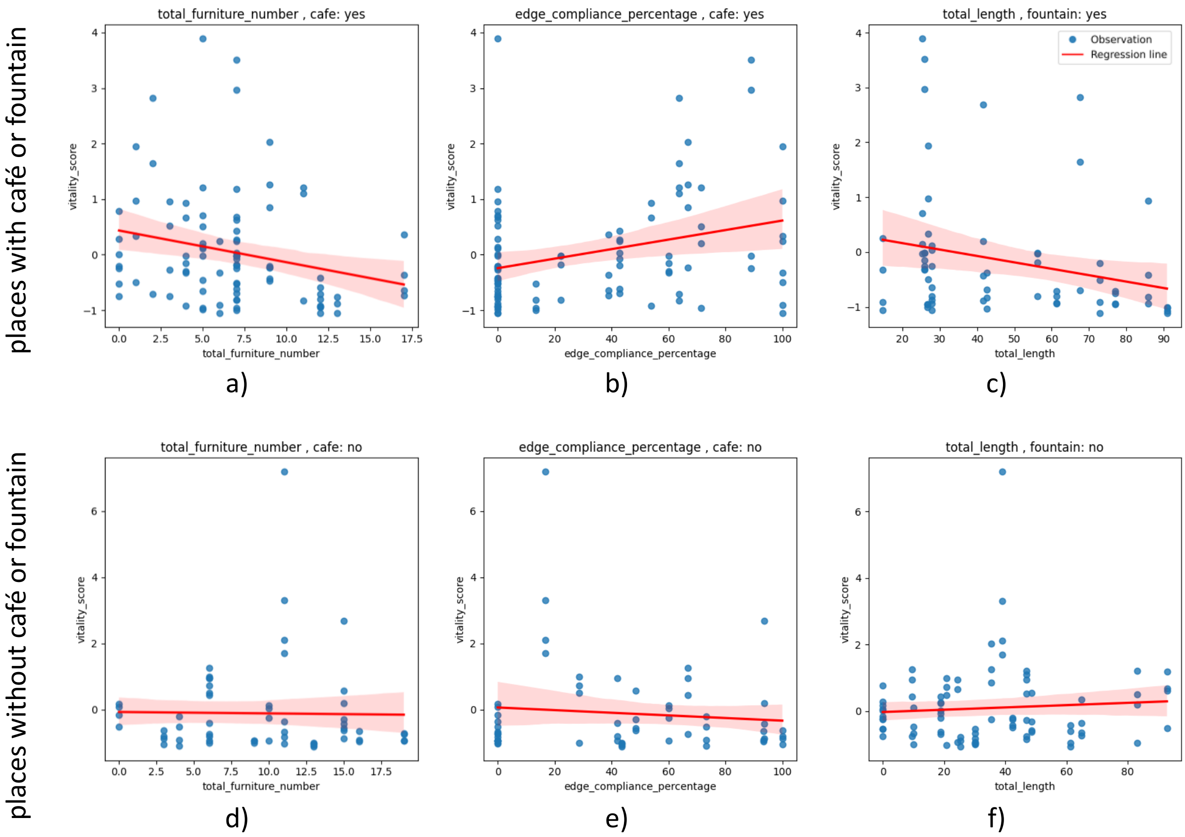


Figure 4-15: Places with a café or fountain show a stronger correlation between seating attributes and place vitality (a, b, c) than places without a fountain or café (de, e, f). Left: impact of the total number of seatings, middle: the compliance to the edge effect, right: the impact of the total seating length.

4.4.5 Summary

Table 4-1 summarizes the results of the multiple linear regression analysis. None of the observed models has a high statistical significance. Controlling by weather, place size, and place attributes increased the significance of each model but didn't allow clear conclusions.

Table 4-1: Coefficients for the correlation between place vitality and seating features controlled in various scenarios.

	number of observations	total_number	edge_effect	social_effect	step_length	ridge_length	bench_length	unique_furniture_types	R^2
Controlled by time									
Model 1: complete	149	-0.04	-	-	-0.02	-0.02	-	0.35	0.076
Model 2: morning	39	-	-	-	-	-	-	-	-
Model 3: noon	39	-0.06	-	-	-	-	-	-	0.106
Model 4: evening	37	-	-	-	-	-	-	-	-
Model 5: Saturday	34	-	-	-	-	-	-	-	-
Controlled by temperature									
Model 6: <15°C	9	-0.07	-	0.01	-	0.01	-	-	0.829
Model 7: 15°C-25°C	90	-0.07	-	-	-	-	0.02	-	0.076
Model 8: >25°C	50	-	0.01	-	-0.03	-0.04	-	0.60	0.340
Controlled by place size									
Model 9: <1500m²	45	-0.08	0.01	-	-0.02	-	-	-	0.343
Model 10: 1500-2500m²	55	-	-	-	-0.06	-	-	0.52	0.223
Model 11: >2500m²	49	-0.11	-0.02	-	-	-0.04	0.04	-	0.342
Controlled by place attributes									
Model 12: with café	91	-	0.01	0.01	-	-	-	-	0.175
Model 13: without café	58	-	-	-	-	-	-	-	-
Model 14: with fountain	66	-0.08	-	-	-0.02	-	-	-	0.113
Model 15: without fountain	82	-	-	-	-	-	-	-	-

However, the results still allow some conclusions about the impact of street seating on place vitality. The total number of furniture was part of six of the eight significant models. In each of these models, the correlation between the number of furniture and the place's vitality was negative. Also, the step-length added to five models with a negative coefficient. Similarly, the count of unique furniture types had a relatively high positive coefficient for three models. The social compliance and bench-length showed positive correlations for two models. The edge effect had a positive correlation in three of four models. While none of these appearances is clearly significant and implications need to be considered carefully, the patterns of significant correlations suggest, that the variety of seating, the bench length, the edge effect, and the sociality of seating had a weak positive impact on the vitality of public places while the total number of seatings and the length of steps had a negative impact on the place vitality. The positive outcomes align relatively well with the existing research about the impact of street seating on the vitality of public places. The negative impact of number of seatings contradicts the findings of Whyte (1980) in his study about small urban spaces in the US.

5 Discussion

This chapter contextualizes the results of this research and connects their implications to the theoretical framework of place theory. Section 5.1 addresses the research limitations and their potential impact on the results. Section 5.2 explores the broader implications for urban planning and future research, while Section 5.3 reflects on the methodology and process, highlighting possible future research directions.

5.1 Research Limitations

Jane Jacobs stated in "The Death and Life of Great American Cities" (1961) that, while observing places, "you might as well listen, linger, and think about what you see". This research derived conclusions solely based on video material which was interpreted by algorithms. Any sensation that goes beyond the shape of trajectories and the count of people was not captured in this research. This might have very well resulted in missing information about the nuisances and advantages of a specific place. For example, only the manual observation of the observed public place in Luhačovice (Czech Republic) revealed a street musician that attracted people to the place, changed the shape of trajectories, and reduced the speed of passing people (See Figure 5-1). A correlation between the street seating configuration and the place vitality therefore can't account for these place-specific features. Also Gehl (1987) highlighted the need to consider the specifications of a side to decide about the details of the place observation. This research only limitedly followed these guidelines by accounting for special events in a place, the weather, and selected place attributes such as the presence of cafés or fountains.

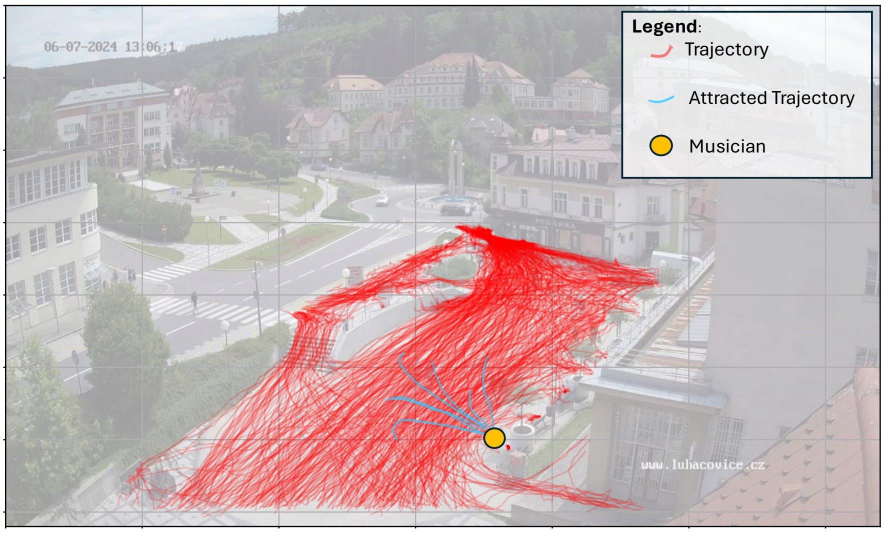


Figure 5-1: A street musician attracts visitors to a public space in Luhačovice (Czech Republic).

This research's limitations also came with the defined scope and the number of observed places. By applying one predefined vitality indicator, the understanding of place vitality was also closely linked to the used vitality metrics. Niu et al. (2022) aimed to rate place vitality as close to the existing literature as possible. Nevertheless, their model is based on the rating of an expert commission. It does not account for vitality metrics that are included in other urban research such as group size and group formation highlighting the interaction of place users (Allahdadi, 2017; Loo & Fan, 2023). The score also doesn't account for the economic and social activities contributing to a vital neighborhood as highlighted in other research (X. Li et al., 2022; Y. Li et al., 2022).

This research included three elements of street seating assessment derived from literature: The edge effect, options to choose from, and socially arranged seating. Furthermore, it included the length of seating elements. Nevertheless, other relevant criteria were not included. Whyte (1980) stressed the need for a good view when sitting. Also Main & Hannah (2009) concluded the importance of “something to see”. Furthermore, some attributes of the seating were not collected. It is for instance not known how comfortable it is, if the seating surface is wet, or if the direct surroundings are pleasant.

Lastly, the observation times and places are limitations of this research. The dependency on publicly available webcams also highly influenced the place selection. Ultimately, places were observed that were seen as relevant by a municipality or tourist agency to install a camera on. The decision criteria are not transparent. It is therefore inherent to a place with a webcam to be “special” in some way. Nevertheless, the observed places showed a wide variety of vitality scores, use cases, and spatial elements.

5.2 Implications of Research

Literature used to motivate the selection of street seating as “the most” relevant street furniture led to the hypothesis, that places have a higher vitality when street seating is arranged in a way that follows public place research and human psychology. However, none of the observed seating attributes showed a significant correlation to the place vitality. The limitations of this research, the selection of the vitality score and the selection of street seating attributes had an impact on the results of the correlation analysis. Nevertheless, all these selection processes have been based on relevant literature and the application of the vitality score on 39 European places gives the results some significance.

Ultimately, the results of this research support the narrative of public place research as summarized by Montgomery (1998). He highlighted the need to see public places in the intersection of the form (spatial elements and the place’s implementation in the urban fabric), the activities in a place, and the image (individual perception). Although written more than 25 years later, this research implies one more time that urban planners and policymakers need to consider places holistically when aiming for vital cities. Placing “good” street furniture might be an element of this, but this research shows that more than this is needed to attract citizens into the public space to use it for more than just necessary activities.

Furthermore, this research applied a trajectory-based vitality metric on a scale that was (to my knowledge) not done before. It therefore also creates implications for the use of algorithmic place analysis. Applying trajectory extraction algorithms on publicly available webcam streams creates a potential in public space analysis (within the aforementioned limitations) that could increase the understanding of public spaces worldwide. A dataset as created in this research can answer questions about, for instance, trajectory patterns, movement speeds, and furniture use within a short timespan while still being resource efficient. These tools can be used by researchers and urban planners to increase the understanding of existing places, to measure the impact of urban place interventions, or to identify underused or overused spaces.

5.3 Reflection and Future Research Directions

Reflecting on the results and methodology of this research allows to pinpoint some of the impactful decisions in this research and their implications for future research.

Based on urban place theories, street seating attributes were selected that showed to be impactful on the use of furniture and herewith relevant to the vitality of public places. This researches only correlated seating attributes to the place vitality but not to the seating use. It therefore has no implications for the impact of street furniture design on the use of the furniture. This suggests that while no correlation was found e.g. between the edge effect and place vitality, there could still be a correlation between the edge effect and the use of street seating.

Furthermore, the selection of the vitality score implies that places are vital when: i) people stay long; ii) the place is used by many people; and iii) they use the place for various activities next to the necessary activities. With these sub-indicators, a place tends to have a higher score when being busy. This is not necessarily the desired environment of people interested in sitting. Reading a book might be more pleasant in a "none-vital" place. Future research could investigate other metrics for "working" places. Aiming for places that support community building and attachment of residents to their spatial and social surroundings might need indicators that aim for a pleasant level of vitality rather than a vitality score that assumes that "more people" results in a better place.

Also, as outlined in the Chapter 2.2, place vitality can be described by other metrics than used in this research. Including POIs that describe social and economic activities in the neighborhood might allow a better impact analysis of spatial elements on the place vitality. Also considering other factors such as the accessibility of the place and the proximity to lively residential neighborhoods might increase the significance of similar research.

On the technical side of this research's methodology, multiple elements could be explored in future research. Chapter 4.2.1 noted frequent false positive detection of human shadows. An extended custom training of the object detection model could increase the precision either by training "shadows" as an extra class or by ignoring detected instances that are upside-down. Also, other tracking algorithms could be explored aiming for fewer ID-swaps or reassigned IDs resulting in a more accurate count of people.

This research utilized automated decision-making (object detection) to create a vitality score of public places. This methodology comes with multiple ethical risks. The observation of people by recording a public place can be seen as a violation of the privacy of individuals. The privacy concerns in this research were relatively low as the webcam position did not allow the identification of individuals and no personal information was stored after the trajectory extraction. Nevertheless, it is not known how and if the official owners of the webcams inform place users about the fact that they are recorded and streamed online when entering the place. Research should question if the used research methodology leads to an increased risk of privacy violations or contributes to the increased availability of methods and infrastructure that enable such violations.

Ultimately, the bias of trained object detection algorithms and their impact on a vitality score needs to be explored more thoroughly. In the past, object detection algorithms have shown to detect people of color with a lower confidence due to a bad representation in the trainings-dataset (Buolamwini, 2023). For this research, a possible implication of such a detection bias could be lower scores for places with a higher density of people of color. It is therefore crucial that the implications of an algorithm-based vitality score as utilized in this research are handled carefully by also considering the possible impact of such automated processes.

By analyzing the impact of street seating on the vitality of public places, this research created an advanced set of methodologies resulting in datasets of human movements in public places. Such a trajectory dataset opens new possibilities for the analysis of public places. Research as done by Whyte, Gehl, and others can be repeated and altered for a wide variety of public places. The dataset allows to investigate speed variations of individuals due to spatial elements and to analyze the use of public places. It can be used to compare the behavior of people in crowds to their behavior in empty places.

Also, a better understanding of seating-use is possible by combining the geo-information of trajectories with the seating data.

Ultimately, the quantitative analysis of street seating and its impact on the place vitality allowed a precise analysis of public places without intruding into the happening in a place as a researcher. By quantifying the qualitative assessment of "how places work," this research highlighted the importance of a holistic approach to placemaking that considers not only spatial elements like seating but also broader factors. By exploring these results with other metrics and optimized methodologies, future research can still improve the understanding of place use to ultimately create a foundation for place design and management that fosters a vital and pleasant urban life to increase the health and happiness of its users.

6 Conclusion

Urban public spaces are crucial to both cities and their citizens, offering places to meet, spend time outdoors, rest, and engage in various activities. These spaces contribute to better social cohesion and identification of citizens to the place. Street seating like benches and chairs are seen as key elements in designing good public places. By giving place-users a place to rest, to meet, and to spend time in a place, the place becomes better used and more vital. Nevertheless, the impact of spatial elements on the use of public places has been mostly assessed from the qualitative perspective. Research and urban planners highlighted the need for more quantitative approaches to understanding public places better, aiming for a public place design that meets the needs of its users.

One key indicator in assessing public places is the place vitality. By counting people, assessing the diversity of activities in a place, and distinguishing between necessary and optional activities in a place, researchers have created methodologies for vitality assessment. Classical approaches need the manual observation of a place and herewith the presence of a researcher in the place. This comes along with high labor and resource intensity of the place assessment. To overcome these challenges, researchers have recently developed methodologies that assess the place vitality based on video material or online available data such as points of interest or social media activities.

This research followed a trajectory-based vitality assessment method developed by Niu et al. (2022). The methodology analyses the trajectories of place users to derive the number of people during an observation period, the duration of their stay, the diversity of trajectories, and the complexity of trajectories. Ultimately creating a vitality score. Such an automated methodology creates the possibility of scaling research to increase the significance of its outcomes.

This research observed 39 European public places by recording publicly available place webcams. Following place theory, places were observed at three different times on a working day (morning, noon, and evening), and during noon on Saturdays. During place recordings, weather conditions were tracked, and it was made sure that the weather was dry. For each place, information about the existing seating was extracted. Following the theory of public places, primary (benches & chairs) and secondary (ridges & steps) seating types were obtained. Furthermore, seatings were classified into their compliance with the edge effect and socio petal seating configurations. The edge effect follows the understanding that seating is more attractive when the back of the user is protected by a wall or greenery, socio petal seating is defined as seating that faces other seating allowing social interactions.

For the extraction of trajectories of place users, the object detection algorithm "YOLOv10" and the tracking algorithm "ByteTrack" were applied. YOLOv10l was custom trained on the "crowdhuman" dataset to increase the accuracy in pedestrian detection and both algorithms were finetuned on the final video dataset. This resulted in a precision of 93.8% and recall of 92.8% for object detection and good results for object tracking. Applying georeferencing based on the homography methodology, the trajectory extraction resulted in a dataset that includes the trajectories in real-world coordinates of each place-user during the observation times.

Ultimately, the correlation of the vitality scores for 149 observations to the seating dataset of each place allowed the analysis of the impact of street seating on the vitality measure for public places. This research aimed to keep the impact of other spatial elements as low as possible by controlling the correlation and multiple linear regression analysis by temperature ranges, the place size, the observed times, and the existence of cafés or fountains. Nevertheless, no statistical model demonstrated a significant impact of street seating on the vitality of public places. Significant variables (p-value < 0.05) of the multiple linear regression models suggest that the total number of seatings has a minor negative impact on the place vitality, while the edge effect, the social setup of seating, and the variety of seating types add slightly positive to the regression model.

The results of this research pinpoint a need for holistic approaches to place design that not only consider single spatial elements such as seating but also takes other factors of and around places into account that might influence the place use. This research also highlights the need to rethink vitality metrics based on the number of people as indicators for “working places” to avoid high vitality scores for busy but unpleasant places. By applying the vitality score to a large-scale dataset, this research showcases the great scalability and accurate results as the main benefit of automated and trajectory-based place assessment. At the same time, it also discusses the need to understand and experience places with all senses. This suggests that future research should investigate more holistic place assessment methods that also take the pleasantness of vital places into account.

7 References

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8 Appendices

A. Object Detection

Object detection is the process of identifying specified objects (objects belonging to a certain class, such as humans, cars, or plants) in an image file. For the processing of video files, this results in the need for object detection in each video frame (Jiang et al., 2019). The literature distinguishes between two kinds of object detection: object detection resulting in bounding box coordinates of the identified object, and Instance segmentation resulting in a set of pixels that belong to the specified class (see Figure Figure 8-1) (Girshick et al., 2014). Instance segmentation results in much more information about the object. Not only the position in pixel coordinates, but also the shape, orientation, and exact size of the object can be extracted. On the other hand, instance segmentation is much slower than object detection. For the extraction of individual pedestrian trajectories, only the coordinates of objects are relevant which is, why this research utilizes algorithms of object detection rather than instance segmentation (Jiang et al., 2019; F.-F. Li & Yeung, 2017; *Object Detection vs. Image Segmentation | by Simay | Inovako | Medium*, n.d.).

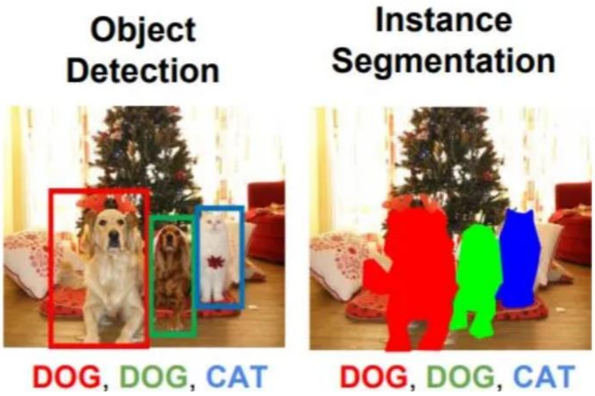

Figure 8-1: The differences between object detection and image segmentation (F.-F. Li & Yeung, 2017).

Object detection is a task that needs multiple domains of computer vision. An algorithm needs to “understand” what is visible on an image. This so-called “semantic understanding of images” is often performed by convolutional neural networks (CNN) (Ibrahim et al., 2020). CNNs for object detection are trained neural networks that can classify sets of pixels into object classes. By running this classification task over every possible set of pixels from an image, probabilities of the class of an object (e.g. ‘human’) and its location (in pixel coordinates) can be extracted. Depending on a set threshold of probability, these objects are detected. As the iteration over every possible set of pixels results in a high computational expense, researchers have further developed pure CNNs by creating multiple levels of semantic image understanding and object location. A typical approach to reduce the complexity of object detection is to use first a mechanism to propose regions of interest, secondly extract the size and location of the objects, and thirdly classify the object into its (predicted) class. By approaching these three steps differently, multiple object detection algorithms were developed. This results in packages such as R-CNN (Region-CNN), Fast-R-CNN (Girshick, 2015), Faster R-CNN (Ren et al., 2016) and YOLO (You only look once) (Redmon et al., 2016). Unlike the other detection algorithms, YOLO processed all three steps in one and herewith became from 2015 onwards an often-used object detection algorithm. Trained on labeled image datasets, YOLO shows high precision and recall while being faster than any other object detection algorithm. In the past years, the team behind YOLO (Ultralytics) improved the speed, accuracy, precision, and user-friendliness of the object detection algorithm constantly. In 2024, YOLOv10 was published with higher precision and speed while being smaller than ever before (A. Wang et al., 2024).

B. Dataset MS COCO

MS COCO stands for "Microsoft Common Objects in Context" dataset (Lin et al., 2014). It is a dataset mostly used for training and benchmarking object detection, segmentation, and captioning algorithms The MS COCO dataset has 91 object types and 328K images, among which more than 200K are label images with 2.5 million instances (Hassan et al., 2024). As the COCO dataset is used for the training of various object detection algorithms, it became an often-used standard for the naming of detection classes. For this research, the only relevant class is the class 'humans' which is assigned to the object category '0'.

C. Dataset crowdhuman

While COCO is a large-scale dataset, it is used mostly to train object detection algorithms for good performance throughout all the 91 classes. While this results in decent results in each of the 91 classes, it also results in a very generalist behavior. To specialize object detection models, training with more specific datasets is recommended. A dataset often used for training for human detection and dense crowds is the crowdhuman dataset (Shao et al., 2018). It contains 15.000 images with a total of 339.565 annotated persons. This results in an average of 23 persons per image which promises good training effects for human object detection models.

D. Steps of Data Processing

1. **Data collection:** Places were recorded in the given resolution and compression algorithm of the webcam stream. These varied between HD and 4K.

2. **Preprocessing of video file:**
   a. Video length was cut to a length of 30min
   b. The resolution was set to HD (1280x720 pixels)
   c. The framerate was set to 15fps

3. **Object detection algorithm**
   a. As object detection algorithm a custom trained YOLOv10l_crowdhuman was used.
   b. The tracking algorithm was Bytetrack.
   c. Output:
      i. Annotated video
      ii. CSV file with trajectories

4. **Trajectory processing**
   a. Trajectories with less than 30 frames were removed.
   b. The center coordinates for each human location (y_max = bottom; x_centre=x_max-x_min) were calculated.
   c. Jittering and outliers were removed by applying a sliding window on human coordinates. Window size = 8.
   d. Real-world coordinates were calculated.
      i. Input files: transformation matrix to transform pixel coordinates into real-world coordinates.
      ii. Real-world coordinates were saved in the system ESPG: 3857.
   e. Trajectories were masked with the place polygons: Coordinates outside of the place polygon were removed (e.g. when on private ground or road).
   f. Again, all trajectories with less than 30 frames were removed.
   g. The complexity (and size) of trajectories was reduced by reducing the resolution of data points from 15 points per second to two points per second. This increased the processing speed of following calculation steps and removed unneeded complexity. Following the methodology of Niu et al. The impact of outliers was reduced by already having calculated the moving average in step 4-c.
   h. A trajectory file in TRA format was created. This was needed for further calculations in Matlab. x and y values are taken from "real_world_sw_x and real_world_sw_y".
   i. A geojson file with all trajectories per place was created. It was used to display trajectories in tools like QGIS or ArcGIS for data validation and visualization.
   j. The walking speed was calculated:
      i. A column with longitude and latitude was added to avoid distortion of the Mercator projection. long and lat were represented in the crs EPSG:4326.
      ii. Speed of pedestrians was calculated based on the time column and "real_world_x" and "real_world_y".
   k. The number of people was calculated for every time of the recording.

5. **Minimum description length calculation:**
    a. Matlab code (Z. Li, 2019) to reduce the complexity of trajectories through the principle of MDL. Input file: TRA file. Output file: Trajectory.csv.

6. **Place vitality score calculation:**
    a. Number of people:
        i. Equal to the count of unique tracker_ids per place.
    b. Duration of stay:
        i. Staying people were defined by people who reduce their speed to a maximum of 0.2m/s for at least 5 seconds
        ii. For each person in the subset of "staying people", the duration of stay (difference in time between first appearance and last appearance in trajectory file) was calculated
        iii. Sum, mean, median, and std are calculated
    c. Trajectory complexity
        i. Calculate the length and angle difference between each consecutive inflection point (MDL) for each trajectory. All differences are summed for the whole place and divided by the number of trajectories.
    d. Trajectory diversity:
        i. Between every trajectory pair the distance matrix was calculated. The structural difference was calculated by comparing the angle and length difference of every element of two trajectories.
        ii. The "best" number of clusters (k) was identified utilizing the silhouette coefficient.
        iii. Hierarchical clustering was applied for k clusters.
        iv. The Shannon entropy was calculated for the trajectories in each cluster. The entropy was summed for the whole matrix (=place)
    e. Ultimately, each vitality score was calculated based on the original vitality model. The vitality scores were z-normalized for every place.

E. Place Overview

Table 8-1: Overview of all observed places specifying observation times and place attributes.

No.	City	weekday	Saturday	Country	morning	noon	evening	Saturday	Residents	Café	Fountain	area [m²]
4	Assisi	05/07/2024	13/07/2024	Italy	X	X	X	X	27600	yes	yes	2243.19
7	Bevagna	04/07/2024	13/07/2024	Italy	X	X	X	X	4800	no	yes	1232.64
8	Biberach	05/07/2024		Germany	X	X	X	-	33500	yes	yes	3232.94
9	Varberg	05/07/2024	13/07/2024	Sweden	X	X	X	X	26000	yes	no	1231.17
16	Wolsztyn	05/07/2024	20/07/2024	Poland	X	X	X	X	13600	no	yes	737.16
20	Kromeriz	05/07/2024	13/07/2024	Czech Republic	X	X	X	X	28000	no	yes	3764.98
45	Montefalco	05/07/2024		Italy	X	X	X	-	5300	yes	no	1277.38
48	Prijedor	04/07/2024	06/07/2024	Bosnia and Herzegovina	X	X	X	X	119000	yes	no	1086.08
52	Schwäbish Gmünd	04/07/2024	20/07/2024	Germany	X	X	X	X	61200	yes	yes	1067.72
61	Sittard	08/07/2024		Netherlands	X	X	X	-	37500	yes	no	1858.97
64	Novi_Sad	03/07/2024	06/07/2024	Serbia	X	X	X	X	389000	no	no	2520.82
67	Trencin-Mierove	03/07/2024	06/07/2024	Slovakia	X	X	X	X	56700	yes	no	1986.12
68	Trencin-Sturovo	03/07/2024	06/07/2024	Slovakia	X	X	X	X	56700	yes	no	1404.59
74	Celanova	03/07/2024	20/07/2024	Spain	X	X	X	X	5600	yes	yes	1593.56
82	Villamartin	03/07/2024	20/07/2024	Spain	X	X	-	X	12000	no	yes	715.61
87	Luhacovice	03/07/2024	06/07/2024	Czech Republic	X	X	X	X	5100	no	no	1232.64
89	Most	04/07/2024	06/07/2024	Czech Republic	X	X	X	X	63800	no	yes	3759.79
90	Pribram	09/07/2024	06/07/2024	Czech Republic	X	X	X	X	32700	no	yes	1911.93
91	Zlin	03/07/2024		Czech Republic	X	X	X	-	74100	yes	no	5595.3
92	Valasske	09/07/2024	20/07/2024	Czech Republic	X	X	X	X	22600	yes	no	2777.75
93	Vrchlabi	09/07/2024	20/07/2024	Czech Republic	X	X	X	X	12300	yes	no	2735.55
98	Szentendre	04/07/2024	06/07/2024	Hungary	X	X	-	X	27600	yes	no	794.85
99	Leicester	08/07/2024	13/07/2024	UK	X	X	X	X	354000	yes	no	3052.9
102	Bielsko_Biala	03/07/2024	06/07/2024	Poland	X	X	X	X	169700	yes	yes	2006.78
103	Brzeg	05/07/2024	06/07/2024	Poland	X	X	X	X	35200	no	no	1715.59
104	Brzesko	04/07/2024	06/07/2024	Poland	X	X	X	X	17000	yes	no	2892.97
105	Brzesko_market	04/07/2024	06/07/2024	Poland	X	X	X	X	17000	yes	yes	3081.17
110	Luban	08/07/2024	06/07/2024	Poland	X	X	X	X	20700	no	yes	2044.83
112	Czersk	05/07/2024	06/07/2024	Poland	X	X	X	X	9900	yes	yes	1801.69
113	Debica	03/07/2024	20/07/2024	Poland	X	X	X	X	45200	yes	yes	2948.32
114	Frombork	05/07/2024	13/07/2024	Poland	X	X	X	X	2300	no	yes	1730.47
118	Jaworzno	09/07/2024	13/07/2024	Poland	X	X	X	X	90300	yes	no	1859.53
119	Jelenia_Gora	08/07/2024	06/07/2024	Poland	X	X	X	X	78300	no	no	1231.17
122	Ozorkow	09/07/2024		Poland	X	X	X	-	19100	no	no	4952.25
124	Swidnik	09/07/2024	13/07/2024	Poland	X	X	X	X	38700	no	yes	2243.19
125	Lublin	10/07/2024	13/07/2024	Poland	X	X	X	X	338500	yes	no	1422.99
126	Lubliniec	09/07/2024	20/07/2024	Poland	X	X	X	X	23500	yes	no	2083.33
128	Myslenice	10/07/2024	01/07/2024	Poland	X	X	X	X	18400	no	no	3232.94
130	Nowy_Targ	10/07/2024	01/07/2024	Poland	X	X	X	X	33200	yes	no	2498.06

Reasons for the exclusion of places at specific observation times:

Evening: 82: stream cancelled after three minutes; 98: Due to the angle of the sun no reliable object detection was possible.

Saturday: 8, 61: Events on place; 45, 91 and 122: Stream not available.

F. Correlation and Regression results:

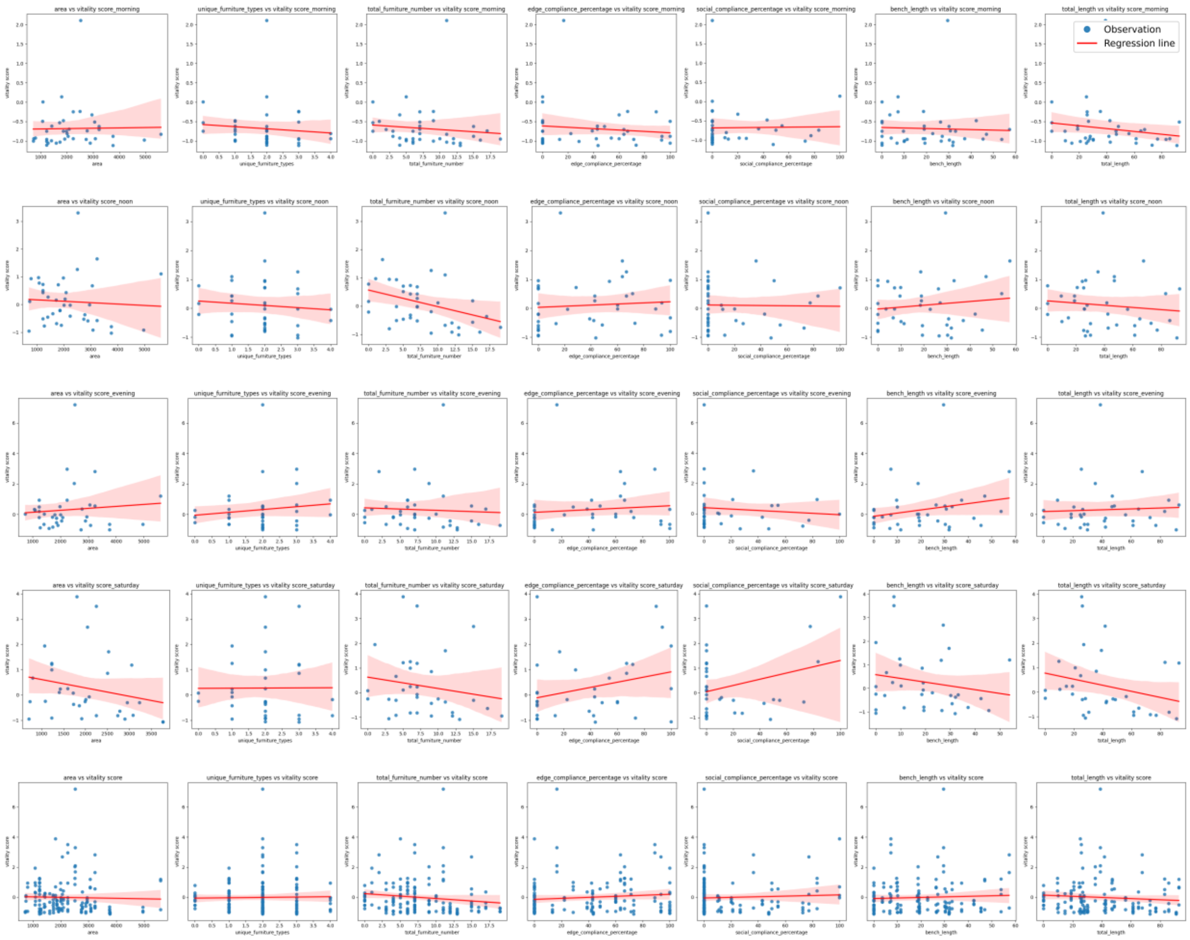

Figure 8-2: Correlation analysis between the place vitality and street seating attributes. First row: morning, second row: noon, third row: evening, fourth row: Saturday and fifth row: all timeslots.

Table 8-2: Regression results for different timeslots.

Data	model	coef (B)	std err	t	p-value	VIF	adj. R^2
model 1: complete	intercept	0.0178	0.238	0.075	0.940	-	0.076
	ridge_length	-0.0193	0.008	-2.289	0.024	2.423	
	step_length	-0.0193	0.008	-2.563	0.011	2.028	
	total_number	-0.0408	0.020	-1.995	0.048	3.337	
	unique_types	0.3487	0.140	2.485	0.014	6.910	
model 2: morning	not significant	-	-	-	-	-	-
model 3: noon	intercept	0.545	0.257	2.198	0.034	-	0.106
	total_number	-0.0587	0.028	-2.093	0.043	-	
model 4: evening	not significant	-	-	-	-	-	-
model 5: Saturday	not significant	-	-	-	-	-	-

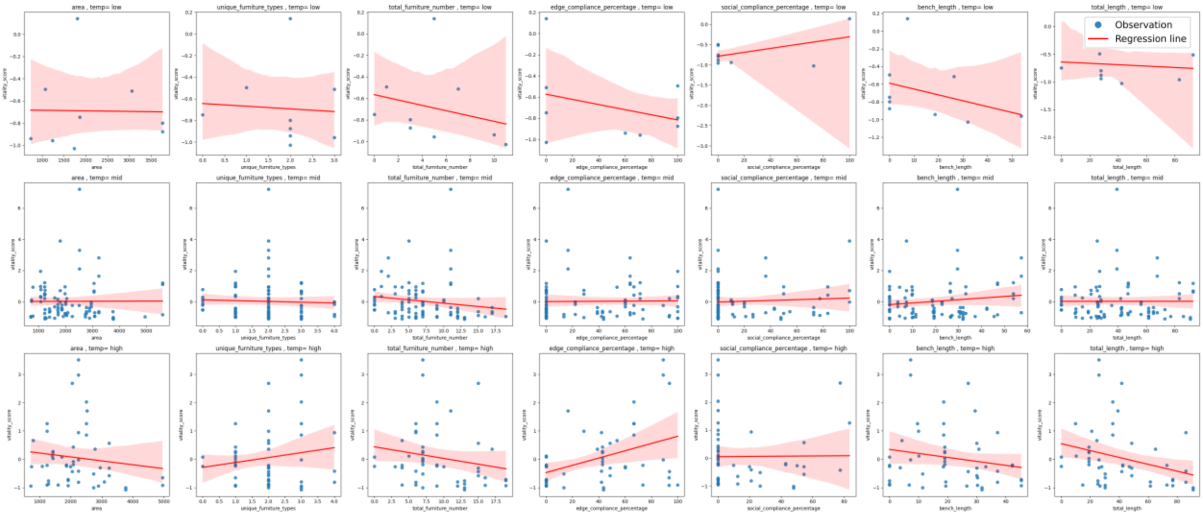

Figure 8-3: Correlation analysis controlled by the temperature: top: low temperature (<15°C), mid: mid temperature (15-25°C) and bottom: high temperature (>25°C).

Table 8-3: Regression results for different temperature ranges.

Data	model	coef (B)	std err	t	p-value	VIF	adj. R^2
model 6: complete, low temp: <15°C, n=9	Intercept	-0.625	0.111	-5.605	0.002	-	0.829
	ridge_length	0.011	0.004	2.997	0.030	1.557	
	Social_compliance	0.008	0.002	4.159	0.009	1.662	
	total_number	-0.074	0.021	-3.579	0.016	2.360	
model 7: complete, mid_temp, 15-25°C, n=90	Intercept	0.149	0.251	0.593	0.555	-	0.076
	bench_length	0.019	0.009	2.198	0.031	2.756	
	total _number	-0.072	0.031	-2.328	0.022	2.756	
model 8: complete, high_temp >25°C, n=50	Intercept	-0.879	0.330	-2.662	0.011	-	0.340
	Edge_compliance	0.010	0.004	2.440	0.019	2.597	
	ridge_length	-0.043	0.014	-3.145	0.003	2.528	
	step_length	-0.026	0.009	-2.773	0.008	2.046	
	unique_furniture_type	0.597	0.206	2.904	0.006	6.523	

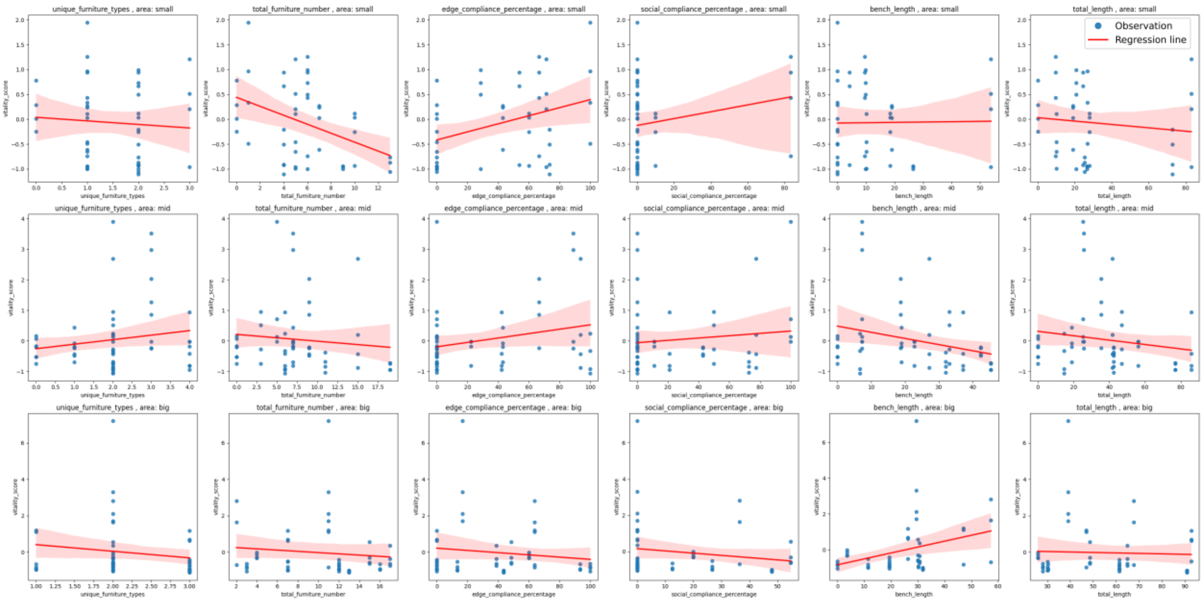

Figure 8-4: Correlation results controlled by the place size. Top: small places (<1500m²), mid: mid sized (1500-2500m²) and bottom: big places (>2500m²).

Table 8-4: Regression results for different place sizes.

Data	model	coef (B)	std err	t	p-value	VIF	adj. R^2
model 9: complete, place_size = small, <1500m², n=45	Intercept	0.171	0.263	0.652	0.518	-	0.343
	edge_compliance	0.010	0.003	3.019	0.004	2.451	
	step_length	-0.016	0.006	-2.784	0.008	1.904	
	total_number	-0.082	0.030	-2.706	0.010	1.537	
model 10: complete, place_size =mid, 1500-2500m², n=55	Intercept	-0.501	0.277	-1.808	0.076	-	0.223
	step_length	-0.056	0.015	-3.641	0.001	2.659	
	unique_furniture_type	0.515	0.152	3.378	0.001	2.659	
model 11: complete, place_size =big, >2500m², n=49	Intercept	1.683	0.733	2.295	0.027		0.342
	bench_length	0.038	0.013	2.916	0.006		3.902
	edge_compliance	-0.020	0.007	-3.005	0.004		1.929
	ridge_length	-0.036	0.011	-3.223	0.002		1.731
	total_number	-0.111	0.042	-2.626	0.012		4.149

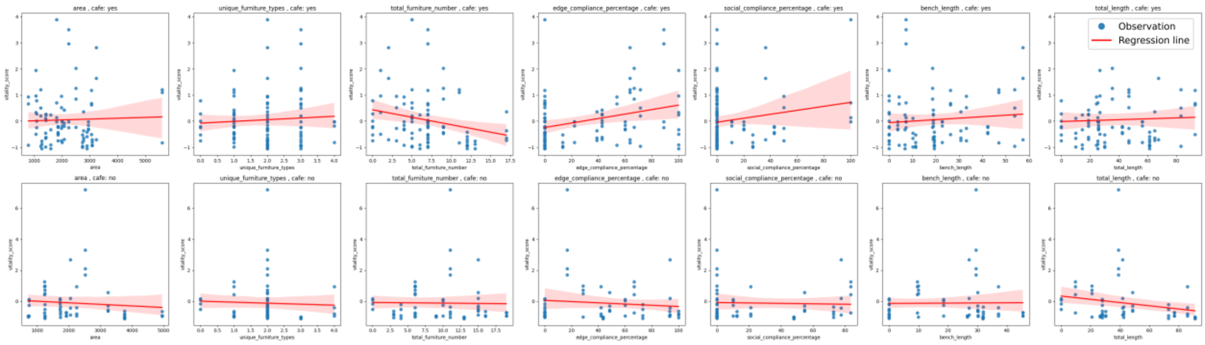

Figure 8-5: Correlation results controlled by café. Top: places with café, bottom: places without café.

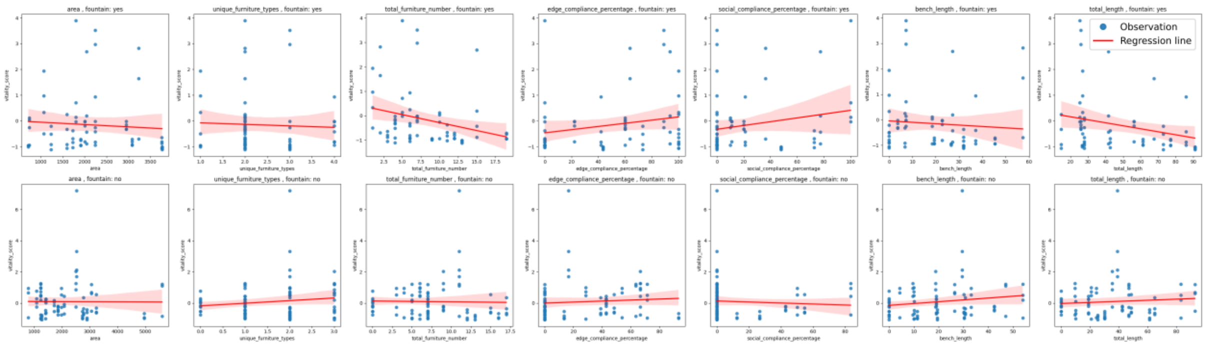

Figure 8-6: Correlation controlled by fountain. Top: places with fountain, bottom: places without fountain.

Table 8-5: Regression results for places with and without café and fountain.

Data	model	coef (B)	std err	t	p-value	VIF	adj. R^2
model 12: complete, with café n=91	Intercept	-0.494	0.160	-3.094	0.003		0.175
	edge_compliance	0.011	0.003	3.888	0.000	1.014	
	social_compliance	0.013	0.004	3.005	0.003	1.014	
model 13: complete, without café n=58	not significant						
model 14: complete, with fountain, n=66	Intercept	0.693	0.299	2.315	0.024		0.113
	step_length	-0.017	0.008	-2.209	0.031	1.297	
	total_number	-0.075	0.028	-2.644	0.010	1.297	
model 15: complete, without fountain n=82	not significant						

Table 8-6: resulting R^2 scores for the multiple linear regression analysis with the sub indicators of the vitality score as dependent variable.

	Number of observations	**R^2_vitality_score**	**R^2_num**	**R^2_dur**	**R^2_TC**	**R^2_TD**
Controlled by time						
Model 1: complete	149	0.076	-	-	0.165	-
Model 2: morning	39	-	-	-	0.117	-
Model 3: noon	39	0.106	0.223	-	-	-
Model 4: evening	37	-	-	-	-	-
Model 5: Saturday	34	-	-	-	0.217	-
Controlled by temperature						
Model 6: <15°C	9	0.829	1	0.705	0.454	0.999
Model 7: 15°C-25°C	90	0.076	0.082	-	0.166	-
Model 8: >25°C	50	0.340	0.303	0.182	0.266	0.291
Controlled by place size						
Model 9: <1500m²	45	0.343	0.217	0.286	0.670	0.306
Model 10: 1500-2500m²	55	0.223	0.254	0.299	0.233	0.131
Model 11: >2500m²	49	0.342	0.383	0.349	-	0.341
Controlled by place attributes						
Model 12: with café	91	0.175	0.128	0.119	0.337	0.131
Model 13: without café	58	-	-	-	0.405	-
Model 14: with fountain	66	0.113	0.076	0.112	0.535	0.063
Model 15: without fountain	82	-	-	-	0.313	-