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Quality of Emerging Data in Transportation Systems: A Showcase of On-Street Parking

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Abstract

With the increasing digitalization and connectivity of transportation systems, there are many opportunities for data-based approaches in transportation planning and management. In this context, data quality management has a special role to play, including the systematic quality assessment of data assets. Data quality is particularly crucial for emerging data that has not yet been widely researched from a quality perspective. Emerging data is often found in Smart Parking Systems (SPSs). Currently, it remains unclear how SPS-generated data can be exploited by potential data consumers, such as municipal parking managers. One reason is the lack of knowledge about the quality of available data sources and the data provided. This paper presents an approach to assessing and defining data quality in the field of on-street parking. It examines relevant quality issues in this field and consolidates the findings into relevant quality indicators. The methodology includes a cross-check analysis of data sources and an inductive taxonomy development. The cross-check analysis provided empirical findings through qualitative analyses of available parking data in Hamburg, Germany, considering various conventional and SPS-based data sources. Based on this, a set of relevant quality criteria and quality metrics was developed.

Keywords: intelligent transportation systems; smart parking systems; data quality management

1. Introduction

In recent years, there has been a growing proliferation of concepts and products in the field of Smart Parking Systems (SPSs), a sub-discipline of Intelligent Transportation Systems (ITS).

SPSs aim to optimize parking infrastructure management and to provide new services for road users. An analog to ITS, SPSs are mainly based on new information and communication technologies, including emerging data sources and data processing methods [1]. In ITS, emerging data sources encompass novel detection and sensing technologies that support a range of traffic management tasks. These sources typically involve advanced technologies, e.g., video image processing, in contrast to traditional data sources, e.g., inductive loop detectors, that have been in use for many years [2]. In the context of parking, emerging data sources include new types of transaction data, parking space sensors and user-generated data.

Data generated by SPSs have the potential to support road travelers who are looking for parking spaces, as well as actors of parking management, usually dealing with the planning and operation of public parking infrastructure [3]. Crucial data for parking managers, such as local parking occupancies, are predominantly collected using costly and error-prone manual methods. Thus, SPS data can complement or even replace existing

collection methods [4]. A concrete use case with SPS-generated data was shown in the context of transport modeling, including an approach to induce new information on parking search patterns in urban road networks [5].

However, the usability of related data sources depends heavily on the quality of data itself, as well as the efforts required to access and process the data. The quality issue has previously been raised in conventional traffic management [6]. It appears to be relevant for parking management as well, with new data sources and technologies arising in the context of SPSs.

To date, there is a notable scarcity of scientific literature addressing the quality of parking data, e.g., quality-related studies or guidelines, as shown in the following literature review. Potential quality questions concern, among other things, the scope, reliability, and value of parking-related data from the perspective of potential data consumers.

This creates a paradox: while more parking data sources are available, clear and complete quality descriptions are missing—making it hard for users to know how to use the data. This paradox has been explored in the sector of Open Data, indicating that the value of a data set is correlated with its quality, and thus should be properly evaluated [7].

To fill this gap, this work elaborates how data in the parking sector can be assessed from a quality perspective. In particular, it presents a recent study on the quality of on-street parking data, including definitions of applicable quality criteria and approaches to assess such criteria.

On-street parking data can be quite heterogenous due to the different methods used for data collection and processing in this sector, along with the complexity of parking situations, especially in urban environments. Thus, it might be challenging to capture quality aspects of heterogenous parking data in one common framework. To gain deeper insights into this issue, this study is based on a cross-check analysis of parking data, i.e., a comparative analysis of several, independent data sources about the parking situation in a real-life urban context. This analysis uncovered specific quality observations and issues, which were then generalized into quality criteria for parking data. These criteria capture various quality aspects via concrete quantitative and qualitative metrics. The criteria were further validated via the data collected.

The work builds upon quality definitions that have been introduced for information systems in general, and for transportation systems, in particular ITS. Such definitions are interpreted and refined for the parking sector, considering specific aspects of the parking system and related data sources.

This work is considered innovative because it builds a quality framework from real-life data using a bottom-up approach, unlike other frameworks that use a top-down method. Another innovation is the integrative quality analysis of multiple data sources, including some emerging sources based on SPS.

The study was conducted in collaboration with the State Transport Authority (Landesbetrieb Verkehr, LBV) Hamburg, which is responsible for parking management in Hamburg, Germany.

This paper is organized as follows: The Section 2 provides a literature review on parking data, looking at existing typologies, typical use cases, and identified quality issues thus far. It also presents previous quality frameworks and definitions in information systems, ITS, and the parking sector. The Section 3 explains the methodology applied, namely the cross-check analysis in Hamburg, Germany, the post-processing of this data, and the derivation of applicable quality definitions. The Section 4 compiles exemplary quality implications from the cross-check analysis, i.e., concrete lessons learned about quality aspects in the analyzed data sources. This section also presents a proposed set

of quality criteria and metrics for the on-street parking data sector. The last two sections discuss and conclude the outcome and applicability of the proposed quality definitions.

2. Literature Review

2.1. Parking Data: Typologies, Uses Cases, Quality Issues

Driven by recent developments in SPSs, parking data exhibits a high degree of diversity in terms of content, use cases, and technologies. To provide orientation in this domain, a taxonomy for parking data was developed, showing how parking data can be classified at different levels [8]. It compiles, among other things, techniques for the collection of parking data, as well as the information content that is covered by parking data. One of the terms in this taxonomy, which is also applied later in this paper, is transaction data, which commonly includes parking fee payment data from parking meters and mobile phone applications. The same taxonomy also provides a categorization of potential functions of SPS-generated data and corresponding data consumers. The main functions identified are proactive parking management, parking usage analytics, and data-driven research on parking behavior. Accordingly, relevant data consumers include parking facility operators, parking supply planners, and researchers in the field of parking.

With parking management as one of the main usage scenarios for SPS-generated data, many studies investigated whether and how emerging data sources generate management-related information, e.g., the local occupancy situation.

Table 1 contains a compilation of the various literature dealing with different data sources and associated use cases.

Table 1. Use of emerging data sources in pilot and research projects about parking.

Data Source	Use Case	Reference
Transaction data (parking meters)	Describe local parking demand including its temporal dynamics	[9–11]
Parking violation records	Derive parking supply data (location and type of on-street parking spaces)	[12]
Smartphone-based data	Record parking events and parking search traffic	[13,14]
Vehicle-based data via ultrasonic sensors	Locate on-street parking spaces and their occupancy	[15,16]
GPS trip data	Determine parking demand and its temporal dynamics	[10]
Satellite imagery and land use data	Map public and private parking supply	[17]
Stationary, on-street sensors	Determine occupancy situation, with statistical methods to identify data anomalies and clusters of sensors with comparable demand patterns	[18,19]
Parking event messages from connected vehicles	Predict occupancy of on-street parking spaces	[20]

With regard to the first data source mentioned, transaction data, all researchers report discrepancies between the actual parking demand and the parking demand derived from such transaction data. Accordingly, there is an under-reporting of occupancy rates in some US cities in the range of 6% to 55% when only transactions are considered [11]. Even after fusing multiple data sources regarding the parking occupancy situation, a significant discrepancy between the measured occupancy situation and the transaction data remains with a correlation level of 0.60 [9]. The "under-reporting rates" or correlation numbers clearly indicate a quality issue.

Most of the other cited studies also reveal quality implications. The accuracy of sensor data is frequently compromised by anomalous measurements, which may result from hardware malfunctions or other sources of error [19]. When processing the sensor

data, such anomalies must be carefully addressed using appropriate outlier detection and correction techniques. GPS data, in particular, provide insights into vehicle trajectories while driving. With careful calibration and filtering, these data can be used to identify individual park search patterns [10]. However, the actual parking event typically remains unrecorded, as GPS devices are often deactivated during stationary periods. Consequently, both sensor and GPS data sources exhibit inherent quality limitations in terms of accuracy and expressiveness.

In any case, quality issues might hinder the intermediate usage by data consumers. In contrast, intense efforts for data post-processing are expected. These efforts include data analytics, fusing various data sources, and properly interpreting the derived information. For a potential data consumer, it is important to foresee such efforts by knowing in advance the quality level of a data source, which is the topic of the rest of this paper.

2.2. Quality Frameworks and Definitions in Information Systems, ITS and the Parking Sector

Traditional quality management focuses on the assessment of individual objects on the basis of quality aspects and the fulfillment of certain requirements in relation to these aspects [21]. Within the assessment, the quality of objects is determined via one or multiple quality criteria (sometimes also called quality characteristics, dimensions, measures, or objects), which explain specific aspects of the object. For practical reasons, quality criteria are often concretized via one or several quality metrics (sometimes called quality indicators). Examples of such metrics include statistical error indicators. A quality framework defines concrete quality metrics to be applied for a certain domain, but also the procedures for quality assessment, i.e., methods and algorithms to determine such metrics. Such definitions are important to promote a common understanding of quality issues in multi-actor environments. This can, for example, support a holistic quality management in a specific organization [22].

Quality definitions have been presented in numerous publications related to the quality management of data and information. A review and consolidation of past definitions works in academia, practice, and industry indicates that finding a common quality understanding among various actors in information ecosystems remains a challenge [23]. As an exemplary reference for the industry sector, quality definitions were established for commercial business environments, including proposals on concrete metrics including calculation methods and examples [24]. A recent consolidation of quality definitions, also based on a literature review, leads to a grouping of the most frequently cited quality dimensions [25].

In the transportation sector, especially for the area of ITS, quality definitions have been further specified. A European ITS stakeholder group developed a quality framework ("EU EIP Quality Package") for the sector of multimodal traveler information services as a concrete ITS application [26]. A similar framework from the USA compiles methods and guidelines for data quality measurement for different applications in road traffic management [6]. In terms of standardization, quality definitions are found in ISO elaborations, namely for the domains of ITS and geodata [27,28]. These works aim to support quality descriptions when providing ITS data or geodata, respectively, via open interfaces.

Some of the literature deals with quality aspects in a data exchange environment, i.e., when data is exchanged between data providers and data consumers via data portals. In the mobility sector, a study examined several US mobility data portals and introduced evaluation metrics for such portals using a Data Portal Evaluation Rubric (DPER). This includes criteria on the openness of the data, the quality of the data set description, user-friendliness, and others [29].

Table 2 compiles relevant quality criteria, as identified in the above references.

Table 2. Relevant quality criteria from the literature.

The Curse of Dimensionality in Data Quality [23]	Data Quality Metrics for Economically Oriented Quality Management [24]	FHWA Traffic Data Quality Measurement [6]	EU EIP Quality Package [26]	ISO/TR 21707:2008 (International Organization for Standardization, 2008) [27]	ISO 19157-1:2023 [28]	Data Portal Evaluation Rubric (DPER) [29]
Completeness Availability and accessibility Currency Accuracy Validity Reliability and credibility Consistency Usability and interpretability	Completeness Freedom from errors Consistency Up-to-datedness	Accuracy Completeness Validity Timeliness Coverage Accessibility	Geographical coverage Availability Timeliness Reporting period Latency Location accuracy Classification correctness Error rate Event coverage Report coverage	Service completeness Service availability Service grade Veracity Precision Timeliness Location measurement Measurement source Ownership	Completeness Logical consistency Positional accuracy Temporal quality Thematic quality	Content relevance Ease of usage Accessibility Visualization Statistical tools application Developer tools Number of data sets Feedback tool Number of data formats Data description Data characteristics Data performance Legal provisions

When comparing the criteria cited in the above references, it is evident that there is frequent overlap, e.g., for "completeness". However, a detailed analysis shows that these references still have very different approaches to grouping and structuring quality aspects. Furthermore, many of these references do not provide guidance on how deploy these quality criteria in real-life assessments.

The cited references are considered generic quality frameworks, i.e., they provide rather universal definitions which need to be concretized to specific (sub-)sectors and use cases of data and information. There are some quality elaborations on subsectors of transportation, such as for roadside traffic-monitoring sensors [30] or crowd-sourced speed data [31]. For the parking subsector, however, only very few references to quality criteria or evaluations are identified.

One study qualitatively assessed various parking data sources based on the following aspects: time, personnel, and financial resources needed to acquire and process data; the geographic coverage of provided data; ability to transfer (or to extrapolate) information from reported locations to other locations; reference to parking demand groups (e.g., residents, employees, etc.); and updatability [10]. The study, however, lacks a further quantification or a scientific validation of such aspects.

Another study assesses the quality of information provided in parking information apps, via a ground truth test in German and US cities [32]. This study examines the correctness of data attributes such as parking locations, price information, etc., if they correspond with findings from the ground truth test.

As another observation, there is little indication of how the cited references are linked to each other. There are some cross-references, e.g., the EU EIP Quality Package refers to the ISO standards [26]. However, no explicit relationships could be found, e.g., how the "completeness" criteria are inherited from one reference to another.

In contrast, this paper aims to establish stronger conceptual linkages. To achieve this, several of the quality criteria and definitions identified in the literature review are revisited and further developed in this paper, specifically adapted as quality criteria and metrics for the domain of parking data. These references are explicitly cited in the subsequent sections. In this way, the proposed framework builds upon and concretizes the generic frameworks

discussed earlier, aiming to ensure conceptual consistency between existing and newly introduced definitions.

3. Materials and Methods

The main method applied in this study was a cross-check analysis, i.e., a comparative analysis of multiple independent data sources about a given subject. Cross-check analyses were previously used to improve the database for mobility studies [33], or to gain quality insights about provided data sets [34].

For the cross-check analysis in this research, data from various emerging and conventional sources were collected in a defined study area in Hamburg, Germany, during the week 12 to 18 September 2022. The focus was on public on-street parking. For the data collection, a sequence of streets in the Hamburg district of Rotherbaum with a total length of approx. 2.1 km was selected. Figure 1 shows the study area as a colored area.

Figure 1. Study area (shown as colored area) for data collection in Hamburg, Germany (© background map: LBV Hamburg).

Various external sources were used and supplemented with a manual survey. This survey is considered the ground truth and is used for comparison with the external sources. Figure 2 symbolically shows the data sources used. The data sources and the collection methods are described in more detail below.

Transaction data were obtained from both parking meters and mobile phone applications. Meter data represent parking ticket sales by meters in the area, each with parking start times and parking durations. Transaction data from mobile phone applications represent ticket sales via mobile phone applications. The data indicate individual start and end times of paid parking tickets and the corresponding mobile phone zone.

Sensor data are provided by ground sensors which have been installed for live occupancy detection at individual on-street parking spaces. The ground sensors were installed as a pilot project for the Hamburg ITS strategy. The sensor operator, T-Systems International GmbH, provided a data set with raw sensor data, as well as a digital map with the sensor installation locations.

Parking API data relates to commercial data services via internet-based, application programming interfaces (APIs). INRIX, Inc. provided access to its parking data API covering the Hamburg study area. The data contain locations and conditions of individual

parking facilities, as well probabilities of finding a free spot at these facilities. The data were retrieved via a REST API in 5 min intervals.

Transaction data from parking meters

Transaction data from mobile phone applications

Sensor data

Parking API

Geoportal Hamburg

Manual survey

Figure 2. Data sources used for cross-check analysis (© Smartparking; INRIX, Inc., Kirkland, WA, USA; Landesbetrieb Geoinformation und Vermessung Hamburg; Peter Lubrich).

The Hamburg Geoportal is a website offering various georeferenced data from the city administration. The data is organized in different data sets, including information on residential parking areas, disabled parking spaces, parking meter locations, and an inventory of public parking space. The data sets are provided as open data, so they could be easily downloaded.

The manual survey followed established procedures, as applied by German municipalities for on-street parking surveys. The study area was divided into 27 street sections, which were observed daily, each at three times of the day. In this way, different demand situations were recorded. Information on both parking supply and parking demand was collected via paper spreadsheets and then processed via Excel. In the surveyed area, 546 public on-street parking spaces were identified.

The data from the mentioned sources was harmonized and overlaid with a Geographic Information System (GIS). A base map from the city administration was used as the GIS basis. Data analyses were performed with QGIS 3.30 software and a PostgreSQL 15.0 database system with a PostGIS extension.

Next, several analyses of the harmonized and overlaid data were conducted. The goal was to generate statements on the local parking situation from the various data sources and to gain insights on their quality, which would subsequently serve as the basis for defining quality criteria. One focus of the analyses was on whether the various data are suitable for determining local parking demand, which is crucial information for parking managers. Specifically, the analysis examined whether and how the data sources can explain the magnitude and dynamics of parking demand over space and time.

The empirical observations from the cross-check analysis were then used to develop a set of quality criteria and metrics in the domain of on-street parking data and corresponding data sources. This approach approximates an inductive taxonomy development which is defined by "observing empirical cases, which are then analyzed to determine dimensions and characteristics in the taxonomy" [35].

As a last step, these criteria and metrics were validated by applying them for the individual data sources used for the cross-check analysis.

4. Results

4.1. Exemplary Quality Implications

4.1.1. The Correctness Issue

This analysis compared how data on parking supply are represented by selected data sources. In particular, locations and amounts of physically available on-street parking spaces were considered, both from the Parking API and Geoportal Hamburg. As a reference, the manual survey was taken as ground truth. The term "available" refers to physical availability, not occupancy. This value can change over the course of the day if parking regulations (e.g., parking bans) apply at certain times of the day.

It was found there are significant differences in the way individual on-street parking spaces are reported. Figure 3 shows a critical example: public parking in a side bay of a main road (shown as a red circle in the figure) is captured quite differently. The manual survey (depicted on the left with a Google Earth snapshot which was recorded one month before the manual survey) reveals marked parking spaces, partially being affected by construction site. The Geoportal shows all theoretical parking sports, implying a higher availability of parking than actually exists. The Parking API does not show any parking spaces at all.

Manual survey	Geoportal Hamburg	Parking API
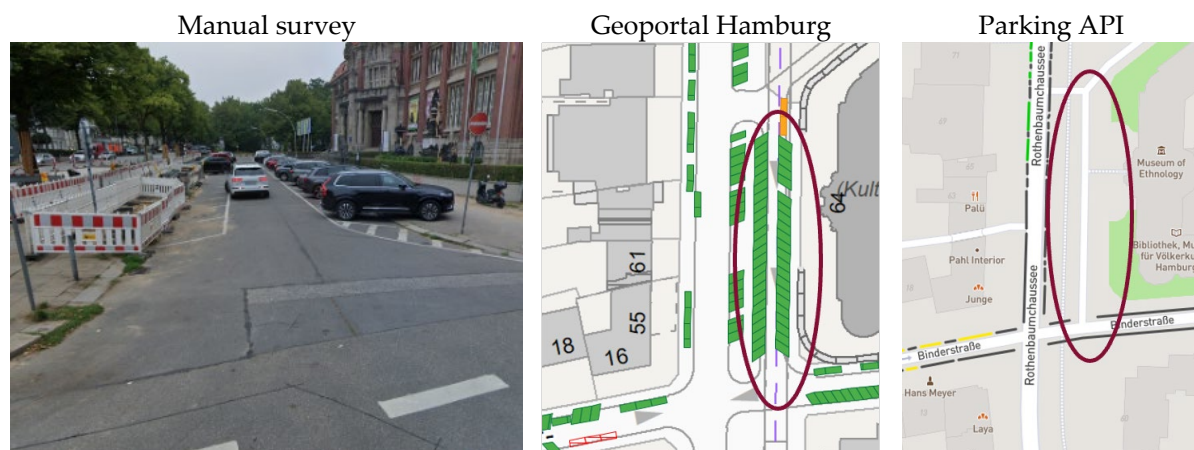
Figure 3. Example on different representations of on-street parking spaces (© 2022 Google; Landesbetrieb Geoinformation und Vermessung Hamburg; INRIX, Inc.).

Similar disparities emerged across various locations in the study area. However, there was no consistent trend that one data source was always better than another one. Upon further examination, several explanations for deviations on reported parking spaces become apparent, including outdated information about unavailable parking due to construction sites, simplifications in parking space declaration in case of unmarked parking, etc.

Figure 4 shows the total number of available parking spaces in the entire area per data source for three different times on one of the days studied. Values from the Parking API are 11% to 16% lower (depending on the time) than the manual survey. The values from the Geoportal, on the other hand, are 7% to 13% higher (depending on the time) compared to the manual survey. However, explicit patterns for such deviations cannot be derived. On the contrary, the deviations vary depending on the road section. In some sections there are no serious deviations at all.
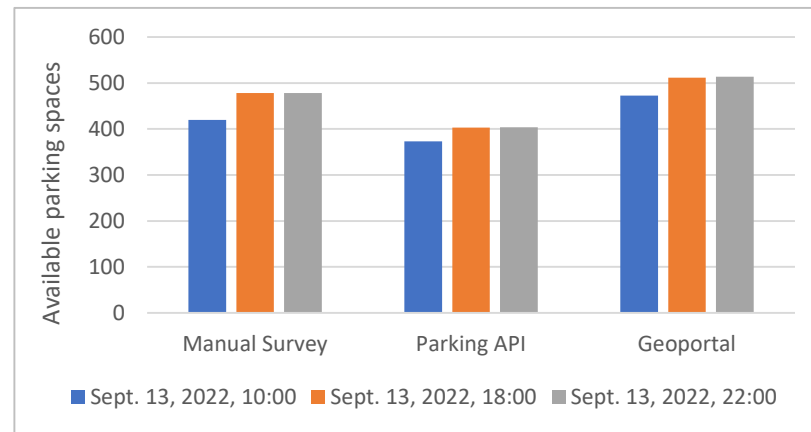
Figure 4. Example of different representations of on-street parking spaces.

Later in this paper, a proposal is given for capturing such deviations via correctness metrics.

4.1.2. The Coverage Issue

The next analysis focused on the content coverage, i.e., the availability and the presentation of certain content elements provided by a data source. A content element might be static information such as the locations of parking spaces, or dynamic information such as occupancy indicators. Content elements can be observed via the data schema, denoting the coverage as well as the structure (e.g., the granularity or the formatting) of individual content elements. Details of such schema analysis were noted in a tabular format. Table 3 shows an excerpt of such analysis.

Table 3. Data schema analysis (excerpt).

	Content Element										
Data Source	Information on Parking Regulations	Parking Fees	Amount of Parking Spaces	Geometry of Parking Spaces	Parking Space Layout	Marked Parking Space	Surface Type	Loading Zones	Spaces Reserved for Disabled	Spaces Reserved for Taxi	Spaces Reserved for Car Sharing
Manual survey	T [1]	N/A	N	N/A	T	N/A	N/A	N	N	N	N
Parking API	Indirectly from fee information	N	N	G (street segments)	N/A	N/A	N/A	N/A	N/A	N/A	N
Geoportal	T	N/A	Indirectly from geometry	G (individual spaces)	T	B	T	G	G	N/A	G

[1] N/A: Not available; T: Textual format; N: Numeric format; B: Boolean format; G: Geometry format.

Accordingly, both the coverage and the structure vary considerably per data source. Looking at the coverage, all data sources are populated differently in terms of content elements. Some data sources (such as the Geoportal) are broadly populated, i.e., they contain a large amount of different information, whereas other data sources are limited to a few content elements.

Data structure also varies by data sources, even if comparable information is available. For example, the time spans for parking regulations are sometimes entered as free text (e.g., "daily 9–20") or as differentiated value pairs (e.g., "Mondays from": "09:00"; "Mondays to": "20:00", etc.). The latter is considered more suitable for automated processing.

Lastly, some data sources reveal the same content elements via different outputs. For example, the amount of available parking spaces can be derived directly from explicit

numbers, or indirectly by counting individual polygons given in a data source. For data consumers, this implies different efforts to data post-processing.

It was further analyzed to which extent certain real-world entities are covered by a data set. In particular, it was tested whether transaction data can accurately reflect the total parking demand over time. Parking transactions from all parking meters located along the manually surveyed route segments were considered. Based on that, average occupancy values per hour were determined, being the average of active tickets for each minute of the respective hour.

For comparison, occupancy data from the manual survey was again considered. Since the survey was conducted only at selected times of the day, the observed occupancy data had to be extrapolated to represent the entire day. This extrapolation was based on relative occupancy profiles derived from a German guideline for calculating parking demand [36]. The guideline provides empirically grounded hourly demand patterns for various municipal settings and traveler types. By combining the survey data with these relative profiles, a full-day absolute occupancy profile for the study area was constructed.

This approach resulted in occupancy profiles, noting average occupancies per hour over one day. Figure 5 shows an example occupancy profile for 13 September 2022.
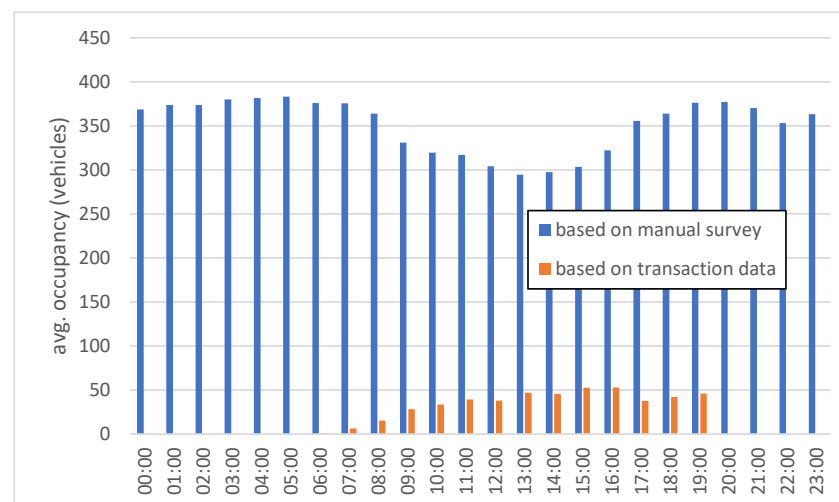
Figure 5. Occupancy profile for 13 September 2022, derived from transaction data (in orange) and from manual survey (in blue).

It is evident that transaction data only explains a small portion of occupancy numbers throughout the day, in comparison to the manual survey. Based on transaction data, the profile shows maximum occupancy values of around 50 vehicles, whereas the manual survey indicates around 350 parked vehicles in corresponding hours. This observation is similar to those of previous studies assessing the suitability of transaction data; see the literature review. The discrepancies in this case are mostly due to non-paying parking customers, in particular residents with resident parking permits. Furthermore, the transaction data has an obvious gap in night-time hours, when parking tickets are generally not mandatory.

From a quality perspective, it is important to identify an adequate measure to explain the observed discrepancies. Consequently, a coverage metric is introduced later in this paper.

4.2. Definition of Quality Criteria and Metrics

4.2.1. Approach

Quality criteria assist quality assessments for one or more data sources. Each quality criterion refers to a single viewpoint; there are usually several such criteria. Each criterion is

associated with one or more metrics, each of which expresses quality values of a quantitative or qualitative nature.

A general prerequisite for quality criteria is that they should have general validity and transferability to different evaluation objects. Thus, different sources of parking data, different types of content data, and different local conditions (e.g., neighborhoods or cities) should be assessable with the proposed criteria.

Further, the criteria definitions need to be related to the type of object being assessed. Previous definitions consider different data levels as assessment objects: attribute values, tuples, relations, as well as entire databases [24]. This approach was simplified by introducing only two levels of assessment objects.

First, a data source as a whole is considered. A source usually provides one or more content data records, and additionally describes higher-level aspects such as the data schema used, access paths to the data, metadata, etc.

Second, a content data record is considered. This usually compiles information about one real-world entity or event, which is defined by the nature of the data source. For example, a data record might be a description of one individual parking facility, a time-stamped report from one parking sensor, etc. Each data record, in return, contains a set of distinct values. For the sensor example, this might be an ID, a time stamp, an event type, etc.

In the following subsections, definitions for individual quality criteria, associated metrics, and associated types of assessment objects are proposed.

Most of the definitions were adapted from previous quality frameworks cited in the literature review. However, these were reframed for the parking sector by revising and concretizing the existing definition attempts.

4.2.2. Coverage and Completeness

A data consumer may like to know whether and to what degree a data source covers the desired data content before obtaining the data. There might be different reasons for the lack of the desired data content: systematic coverage gaps due to the detection methods, e.g., because some required data is never measured, or incomplete data, e.g., because of temporary interruptions of detectors. Thus, there are different approaches to capturing coverage and completeness, each represented by a different metric. The following definitions are roughly based on the quality criteria listed in the EU EIP Quality Framework [26].

First, it is interesting to understand the coverage of content elements in any given data source. In the cross-check analysis, it was discovered that each of the data sources covers different content elements in their data schemas. For example, some data sources offer localization data on individual parking spaces, whereas other data sources do not offer such localization at all, or only indirectly or on an aggregated level.

A Content Element Coverage Rate (CECR) is introduced. This provides a numerical statement of whether and how certain content is available, according to the given data schema; see Equation (1).

$$Q_{CECR} = \frac{\sum_{C_1}^{C_n} e_i w_i}{\sum_{C_1}^{C_n} w_i} \tag{1}$$

where

C_i: content elements $C_1, C_2, \ldots, C_n$;

$e_i \in [0; 1]$: relative expressiveness of C_i;

$w_i \in [0; 1]$: relative weight of C_i.

The expressiveness e_i states whether an information element is present at all within a data source. In the case it is present, it says whether a direct or an indirect statement

about the information element is possible, based on the input value. The latter is the case if the desired information must be derived or interpreted from the input value by the data consumer.

For the expression of e_i, the following values are proposed in Table 4. The intermediate values 0.3 and 0.7 are defined intuitively but can be determined based on the specific needs of the data consumers.

Table 4. Values of the expressiveness parameter for the Content Element Coverage Rate metric.

Values of e_i	Definition
1	Content element can be used directly without conversions and interpretations.
0.7	Content element must be converted (e.g., from a string to a float value).
0.3	Content element must be interpreted (e.g., the "number of parking spaces" must be derived from a geometric value).
0	Content element is not available.

The relative weight w_i can be used to consider whether and with which priority the data consumer requires certain content elements, e.g., because these elements are required for certain services or analyses. In that sense, the values w_i are to be specified by the data consumer.

Second, another coverage metric is derived from the above-mentioned observation that transaction data only represent a portion of total parking demand. It is therefore important to capture two dimensions: the discrepancy of reported entities and the temporal trend of such discrepancies, as evidenced by the hourly occupancy profiles presented.

For this reason, a Temporal Occurrence Coverage Rate (TOCR) is introduced. This provides a numerical statement of whether a certain real-life occurrence is reported in a temporal context, whereas an occurrence might be an entity or event (ideally represented as a data record); see Equation (2).

$$Q_{TOCR} = \sum_{t_1}^{t_N} \frac{r_i}{e_i} / N \tag{2}$$

With
t_i: a time unit;
N: total of time units;
r_i: number of occurrences being reported per time unit i;
e_i: number of occurrences in reality per time unit i.

This metric first considers the ratios of reported vs. expected amounts of occurrences per assessed time unit and then harmonizes the sum of these ratios for all time units under assessment.

Third, completeness is understood in terms of the existence of data records, in comparison to the expected amount of data records. A Data Record Completeness Rate (DRCR) is introduced; see Equation (3).

$$Q_{DRCR} = \frac{r}{e} \tag{3}$$

With
r: reported amount of data records;
e: expected amount of data records.

All three metrics are calculated at the level of a data source. The output value of these metrics is in the range between 0 and 1.

Looking at the latter metrics, it is necessary to clarify the difference between the coverage metric Q_{TOCR} and the completeness metric Q_{DRCR}. Q_{TOCR} is considered an ex

ante measurement. Referring to the previous example where transaction data excluded some portions of parking demand, this measure will ex ante capture such exclusions. The circumstances behind such exclusions (e.g., the fact that resident permits are never captured by transaction data) should be noted with this metric to explain to the data consumer the reasons behind deficient coverage. In contrast, Q_{DRCR} explains any missing data records which are supposed to be ex post present in a data source. For example, when only a portion of installed sensors provide data in a data source, perhaps due to temporary malfunction, this metric will account for this portion. It is subject to change over time and should be measured regularly.

4.2.3. Correctness

Correctness is the deviation of the data in a data source compared to reality. In the area of parking data, deviations are almost always to be expected due to the dynamics of parking conditions. Thus, the magnitude of deviations is mostly relevant when describing the correctness. For this purpose, various statistical metrics explaining the existence and character of deviations are introduced. Such statistical metrics are also found in other literature dealing with quality assessments in transportation. For example, a recent quality evaluation of Floating Car Data in Thessaloniki, Greece, is based on the same concepts and metrics as proposed below [37].

One starting point is the percentage deviation of value pairs. The deviation is to be calculated by comparing a ground truth and a comparison data offer, which is the data source under assessment. Thus, the ground truth will provide measured values m_i, and the comparison data comparative values c_i.

The calculation of a percentage deviation depends on the definition of the aggregate for which the deviations are calculated. In the above example from the cross-check analysis, deviations on available parking spaces for the entire area were shown. However, these aggregate numbers are biased as they do not reveal some small-scale or local effects. For example, c_i values might be higher than m_i values in one street segment, and vice versa in another street segment, so the area aggregate would even out both deviations.

Consequently, statistical metrics are used to examine how individual value pairs differ within a single data set.

The Mean Absolute Error (MAE) and the Root Mean Squared Error (RMSE) consider the average error in the comparison between m_i and c_i; see Equations (4) and (5).

$$Q_{MAE} = \frac{1}{N} \times \sum_{i=1}^{N} |m_i - c_i| \tag{4}$$

$$Q_{RMSE} = \sqrt{\frac{\sum_{i=1}^{N} \left((m_i - c_i)^2 \right)}{N}} \tag{5}$$

Both metrics are determined in the range between 0 and ∞ and are independent of the error direction. They are negatively oriented values, which means that lower values are better. However, with RMSE, taking the square root has an interesting effect: since the errors are squared before being averaged, RMSE gives high weight to large deviations. This underscores the special importance that RMSE holds in highlighting large deviations.

The metrics introduced above can now be calculated for any pair of values. A common use case will be parking space counts (either as capacities or occupancies) in areas or street segments.

However, these metrics neglect the fact that the spatial units under consideration can vary greatly in parking capacity, which in turn can affect the quality score. For example, a deviation of 5 parking spaces is significant for a facility with a total of 20 parking spaces,

while the same deviation is tolerable for a facility with a total of 200 parking spaces. Thus, it appears useful to employ a metric that evaluates deviations differently for "small" facilities compared to "large" facilities.

A variant of the above RMSE metric considers the size of the parking supply in the spatial unit to be evaluated. The quantity used is not the parking capacity, as this may be unknown, but the length of the street segment that applies to the value pair under consideration. Such lengths are usually easy to determine since data about on-street parking is often georeferenced to a street network including length information.

The length-weighted variant of the RMSE metric is formulated as Equation (6).

$$Q_{RMSE-weighted\ by\ length} = \sqrt{\frac{\sum_{n=1}^{N}\left(\frac{(m_n - c_n)^2}{L_i}\right)}{N} \times \frac{\sum_i^n L_i}{N}} \tag{6}$$

With

L_i: length of street segment.

In the case of off-street parking facilities, such as parking lots, the street segment length could be replaced in the formula with an area figure.

Overall, some, or even all of the previously mentioned metrics, can be used for the correctness evaluation of individual data sources.

4.2.4. Timeliness

In terms of temporal aspects of data quality, there are two different concepts: the timely availability of data, and the freshness (or aging) of data.

The first concept captures the time offset for data availability, i.e., the time after which a data consumer can retrieve requested information. A metric $Q_{Availability\ Latency}$ is proposed, defined as the time lag between the temporal validity of content data and the time of (earliest) availability to the data consumer.

This metric is highly relevant if the data is provided via automated interfaces, e.g., via an API, and has a real-time component. In such a case, temporal dynamics have to be considered when calculating the metric. For example, for a data offer with real-time parking availability from sensor installations, it is recommended to measure $Q_{Availability\ Latency}$ several times (e.g., for each sensor message), and to provide statistical values (e.g., as mean values or 95% percentiles for the last month).

The age of the data considers the probability that values are still up to date when being assessed. Such probability has two influences: the data collection date, derived from the temporal reference of the content data; and the decline rate, determining the portion of attribute values which is expected to be outdated in the time span between the data collection date and the date of assessment. The latter aspect is considered relevant for parking data, as there might be significant differences in decline rates depending on the data type, i.e., image parking availability data with a high decline probability vs. parking fee data with a lower decline probability. Former definitions are reused which apply a probabilistic approach to capture the influences of the data collection date and the decline rate [38].

Accordingly, the metric $Q_{Currency}$ is introduced on the data record level; see Equation (7). This metric examines the currency levels per content element (each in the range between 0 and 1) and averages them across all content elements. Both inputs, decline rates and ages should be of the same temporal unit (e.g., years). It is proposed to apply

average values for these inputs from, e.g., empirical evidence. This metric is rather suitable for data that are collected once and provided retrospectively.

$$Q_{Currency} = \frac{\sum_{C_1}^{C_n} e^{-decline(C_n) \times age(C_n)}}{N} \tag{7}$$

With

C_i: content elements $C_1, C_2, \ldots, C_n$;

N: total of content elements.

4.2.5. Exploitability

In addition to data-inherent aspects addressed by the previous criteria, it is worthwhile to explore data-subsistent aspects such as data access and reuse. These are less concerned with the data content itself and rather more focused on the abilities and possible efforts required for data consumers to obtain the data and utilize it for their own purposes.

Depending on the data sources, data access can be straightforward and self-explanatory or, on the other hand, time-consuming and requiring explanation. Data reusage refers to the ability of a data consumer to analyze the obtained data or to build services using the obtained data. This capacity can be either unrestricted or, conversely, subject to limitations.

Corresponding quality metrics are defined next, based on the previous Data Portal Evaluation Rubric (DPER) [29].

$Q_{User\ Friendliness}$ describes the usability of the access route to the data, e.g., is the content data sufficiently described via metadata?

$Q_{Organizational\ Effort}$ describes the organizational requirements for obtaining and utilizing the data, e.g., are standard licenses used?

$Q_{Technical\ Effort}$ describes the technical requirements for obtaining and using the data, e.g., is the API well documented?

These three metrics describe a data source via statements about the presence of certain features f_i. They state whether a particular feature is present ($f_i = 1$) or not ($f_i = 0$). The statements are based on the usefulness from the point of view of the data consumer, so a "1" means a positive, and "0" a negative consumer experience.

Each of these three metrics is formed by the sum of such statements; see Equations (8)–(10).

$$Q_{User\ Friendliness} = \sum_{i=1}^{n} f_{Ui} \tag{8}$$

$$Q_{Organizational\ Effort} = \sum_{i=1}^{n} f_{Oi} \tag{9}$$

$$Q_{Technical\ Effort} = \sum_{i=1}^{n} f_{Ti} \tag{10}$$

Features f_i are defined as follows in Tables 5–7. In practice, a specific weight could be added to each feature, accounting for specific needs of data consumers. For example, the existence of an API (f_{T1}) could be prioritized over the corresponding API documentation (f_{T2}). For reasons of simplification, the formulae above do not include such a weighting.

Table 5. Feature definition for user friendliness.

Feature	Definition
f_{U1}	Metadata is listed on an online portal.
f_{U2}	Metadata can be searched via an online portal.
f_{U3}	Content data can be searched via an online portal.
f_{U4}	Content data can be filtered via an online portal.
f_{U5}	There is a preview of the content data via an online portal.
f_{U6}	There are statistical functions for analyzing content data via an online portal.

Table 6. Feature definition for organizational effort.

Feature	Definition
f_{O1}	Standard licenses are used (e.g., Creative Commons licenses) or the data can be used without any legal restrictions.
f_{O2}	No contracts need to be concluded between the data provider and the data consumer.

Table 7. Feature definition for technical effort.

Feature	Definition
f_{T1}	A web-based access mechanism (e.g., a programming interface/API) is available.
f_{T2}	A web-based access mechanism (e.g., a programming interface/API) is documented.
f_{T3}	Standard data formats are used.
f_{T4}	Data access is unlimited in terms of data volume and the number of data retrievals.
f_{T5}	Transparent information is provided on calculation methods and original data sources.
f_{T6}	Technical support is available.

4.2.6. Validation

The quality criteria and metrics, as introduced above, were validated using real data sources from the Hamburg cross-check analysis. As much as possible, all metrics were formulated as concrete quality statements for all examined sources or their data records.

The metric Q_{CFCR} was determined based on data schema from the manual survey, the Parking API and the Geoportal, which contain a range of content elements. The relative weights w_i were arbitrarily set. In a real quality assessment, these would have to be agreed upon in advance with real data consumers. Table 8 compiles the Q_{CECR} results. It is obvious that the Parking API achieves the highest ranking, mostly because it presents most content elements in a direct way.

The Q_{TOCR} metric was calculated from the above comparison of parking demand represented by transaction data vs. the total parking demand. Using data from 13 September 2022, the metric is calculated as 0.062, indicating a rather poor coverage.

The Q_{DRCR} metric was based on parking meter data. It was checked whether all parking meters physically located in the study area were also covered in the corresponding data set. In fact, out of the 23 m, one was missing from the data set, resulting in the metric calculation of 0.957.

Below, various correctness metrics for data from the Parking API and the Geoportal are documented. The focus of this analysis was the number of legally available parking spaces, i.e., the net capacity. The measured values m_i are based on the manual survey, while the comparative values c_i are based on Parking API and the Geoportal, respectively. The

analysis considers 36 street segments as spatial units, i.e., 36 value pairs are compared. Table 9 compiles the correctness metric results.

Table 8. Content Element Coverage Rate results.

Data Source	Expressiveness e_i Per Content Element									Q_{CECR}
	Location ($w_1 = 1$)	Access Conditions ($w_2 = 1$)	Payment Methods ($w_3 = 1$)	Capacity ($w_4 = 1$)	Resident-Only Restrictions ($w_5 = 0.5$)	Loading Bays ($w_6 = 0.5$)	Disabled Parking ($w_7 = 0.5$)	Taxi Stands ($w_8 = 0.5$)	Car Sharing Stands ($w_9 = 0.5$)	
Manual survey	0.5	0.5	0	1	1	1	1	1	1	4.08
Parking API	1	1	1	1	1	0	1	0	1	5.08
Geoportal	1	0.3	0.5	0.3	0	0.5	0.5	0	0.5	2.64

Table 9. Correctness metrics results.

Data Source	Q_{MAE}	Q_{RMSE}	$Q_{RMSE-weighted\ by\ length}$
Parking API	11.17	15.84	14.58
Geoportal	5.19	6.18	6.25

Here, the peculiarity of $Q_{RMSE-weighted\ by\ length}$ becomes clear: the Parking API is rated worse than the Geoportal in all cases, but the gap of the quality values decreases with $Q_{RMSE-weighted\ by\ length}$, as the length weighting relatively improves the rating for the Parking API.

The metric $Q_{Currency}$ was captured exemplarily for the Geoportal data source. The temporal reference for this source is unknown: the corresponding metadata only refer to "continuous updating." Based on internet research, a parking data collection campaign by the City of Hamburg was carried out in 2015. Thus, the age of the Geoportal data is assumed to be 7 years, when taking the 2022 analysis as the reference point. Decline rates for selected data elements presented by the Geoportal were also assumed. In practice, they should be quantified from sample tests.

Table 10 compiles the $Q_{Currency}$ results. This example reveals the influence of data elements with high decline rates (in particular, capacity), significantly decreasing the overall average result for the entire data source.

The metric $Q_{Availability\ Latency}$ could only be partially captured. The manual collection further imposed a manual data post-processing time of approximately one week, which is equivalent to the availability latency. For the Parking API, the latency is close to zero, as the API provides a nearly latency-free data response for any data queries (subject to technical delays due to web services, etc.). Availability latencies could not be quantified for the transaction and sensor data because all data sources were obtained with a certain time lag relative to the period of 12–18 September 2022. In practice, however, minimum latencies are expected, but these would need to be independently verified with the data providers.

Table 10. Currency results for the Geoportal data source.

	Content Element C_n								
	Location	Access Conditions	Payment Methods	Capacity	Resident-Only Restrictions	Loading Bays	Disabled Parking	Taxi Stands	Car Sharing Stands
age (C_n) (years)	7	7	7	7	7	7	7	7	7
$decline(C_n)$ (1/year)	0	0.5	0.3	2	0.3	0.5	0.5	0.5	0.5
$e^{-deline*age}$	1.000	0.030	0.122	0.001	0.122	0.030	0.030	0.030	0.030
$Q_{Currency} = 0.155$									

Finally, the exploitability metrics were determined by checking the presence or absence of certain features. Overall, the calculation appears straightforward due to the binary characteristics of such features. Table 11 compiles the exploitability metric results. As a result, the Geoportal appears to be the best rated data source.

Table 11. Exploitability metrics results.

Data Source	f_{U1}	f_{U2}	f_{U3}	f_{U4}	f_{U5}	f_{U6}	$Q_{User\ Friendliness}$	f_{O1}	f_{O2}	$Q_{Organizational\ Effort}$	f_{T1}	f_{T2}	f_{T3}	f_{T4}	f_{T5}	f_{T6}	$Q_{Technical\ Effort}$
Transaction data (parking meters)	0	0	0	0	0	0	0	1	1	2	0	0	0	1	0	0	1
Transaction data (mobile phone applications)	0	0	0	0	0	0	0	1	1	2	0	0	0	1	0	0	1
Sensor data	0	0	0	0	0	0	0	0	0	0	1	0	0	1	0	0	2
Parking API	1	0	1	1	1	0	4	0	0	0	1	1	0	0	0	1	3
Geoportal	1	1	1	1	1	0	5	1	1	2	1	1	0	1	0	1	3
Manual survey	0	0	0	0	0	0	0	1	1	2	0	0	0	1	1	0	2

5. Discussion

This study established a foundation for quality assessment in the domain of parking data by defining applicable quality criteria and associated metrics. Such quality definitions aim to enable data providers to make robust quality statements about the data sources they are offering, and to empower potential data consumers to evaluate a data source before procuring the data. Furthermore, the criteria and metrics aim to enable the comparison of different data sources.

The quality definitions come from a cross-check analysis, i.e., a comparative analysis of parking data in Hamburg, Germany. Six independent data sources were compared and analyzed with respect to pre-defined research questions. The focus was on new types of data sources, particularly transaction data, sensor data, and data from a commercial Parking API. This analysis resulted in various findings regarding the coverage, informative value, and other quality aspects of parking data. Further, a set of universal quality criteria

and quality metrics was derived from this analysis. Finally, the proposed quality metrics were validated by applying them to the analyzed data sources in the cross-check analysis.

The validation provided some quantitative and transparent statements about the quality of the studied data sources. In most cases, unambiguous and interpretable values could be calculated. Considering the significant quality discrepancies identified for the data sources in Hamburg, the metrics can adequately capture such quality variations. Overall, the proposed quality criteria and the corresponding metrics appear to be suitable for future quality assessments in the on-street parking sector.

The validation further revealed no single data source with overall "best" quality levels. Instead, all the sources have some pros and cons when looking at specific metrics. For example, data from the Geoportal appears to have good coverage, but demonstrates some weaknesses regarding its up-to-datedness. Eventually, it depends on the individual assessment of a data consumer to find a preference for a particular data source, based on prioritization of certain metrics or on minimum values for some metrics. A possible scenario for data consumers may be that two or more data sources need to be obtained and combined to meet their quality needs.

There is a lingering concern regarding defining the ground truth. Throughout the cross-check analysis, the manual survey values were often used as reference values in the calculation of quality metrics. However, it is unrealistic to assume that the manual survey is error-free and can be used unambiguously. For example, in certain street sections, it was not always straightforward to quantify the number of available parking spaces due to, for instance, unmarked spaces. Furthermore, the occupancy situation can change continuously during the survey and distort the survey results. Overall, a certain degree of uncertainty remains in reference values.

In practice, it is recommended to pay special attention to the trustworthiness of the ground truth source. This might include, e.g., a double reporting and inter-rated agreement tests to identify the extent of disagreement. It is also recommended to take account of such uncertainties when providing related quality criteria, e.g., by performing sensitivity analyses and by calculating related metrics as ranges.

6. Conclusions

The work presented follows an approach that other researchers have found beneficial for assessing data in unexplored data domains [7]. More concretely, it applies a bottom-up methodology to define relevant quality aspects in the data domain of on-street parking, based on concrete data exploration.

As a result, the work provided a specialized quality framework for on-street parking data, in contrast to rather generic quality frameworks which have been presented before. Such specialization considers unique characteristics of data sources and data contents, which might be neglected in generic quality frameworks. In this way, the presented work provides a ready-to-use basis for quality assessments in the field of on-street parking.

An open question remains regarding the generalizability and transferability of the proposed framework beyond the Hamburg case study. Initial evidence suggests that the quality metrics introduced here may also be applicable in other contexts. For instance, the European NAPCORE project has developed several innovative quality frameworks for various ITS domains [39]. Notably, the NAPCORE framework for Floating Car Data (FCD) employs the same correctness metrics as those proposed for parking data and validates them in Thessaloniki, Greece [37]. Nevertheless, further validation of the proposed parking quality metrics in additional contexts appears necessary.

Thus, it is recommended to extend the validation tests for the quality criteria pro-posed in this paper to include other locations, such as cities with different sizes and different

characteristics, and with alternative management schemes. This might result in further findings if other local settings affect quality assessments for parking data. Further validation should also include additional types of parking data sources, or a larger sample of data with longer observation periods to account for the fact that parking demand may depend on seasonal effects or other factors. Moreover, the proposed quality definitions might be expanded or converted to similar sectors, such as off-street parking, park and ride facilities, or other elements of the transportation system.

For incorporating the proposed quality framework into the routine operations of organizations, we give the following three recommendations.

First, it is essential to identify relevant data consumers and use cases, which is recommended by other frameworks as well [6]. This implies that the proposed quality framework must be further specified by selecting appropriate quality metrics, defining methods for calculating and documenting these metrics, and establishing acceptable or target levels for each.

In this context, it is worth noting that the "right" levels of data quality are context-dependent: they are influenced both by the capabilities of data providers—such as technological maturity in data collection and processing—and by the specific requirements of data consumers. The specific requirements for parking data access will vary significantly depending on the type of data consumer. For instance, a developer of an online information service may require real-time data on parking availability with minimal latency. In contrast, an infrastructure planner may prioritize comprehensive historical data on parking demand over the past several years, where low latency is less critical.

In this sense, an intense dialog between data providers and data consumers is suggested via quality workshops conducted at stakeholder organizations, dedicated quality evaluations as part of pilot projects, and systematic data requirements analyses on the data consumer side. In this process, any weighting factors applied to the proposed quality criteria should be conclusively determined, replacing the arbitrary or intuitive settings used in this study. These weighting factors should be grounded in specific expectations and requirements of data consumers or derived from empirical evidence obtained through future quality assessments.

Second, quality criteria should be considered alongside metadata, which ideally accompany any publicly available data source [6]. These provide additional information about the data provider, the geographical reference, licensing conditions, and more. In this way, (potential) data consumers can use both quality criteria and metadata to assess the suitability and quality of a data source for their purposes. Various efforts have been made to include quality information in metadata descriptions [40]. It is recommended to adopt a similar approach for parking data, i.e., to describe quality levels of parking data sources via metadata.

Third, it is important to recognize that data quality assurance is typically embedded within broader data management or data governance frameworks. These frameworks also address other aspects of data handling, such as storage, sharing, update policies, and data disposal. This implies that processes and responsibilities for managing and governing data are already established and well-structured. Several guidelines on data management and governance for traffic management stakeholders have been published [41,42]. One key recommendation is to ensure transparency in data quality, for example, through regular audits and reporting. It is therefore advisable to adopt similar practices within the parking management sector.

Abbreviations

The following abbreviations are used in this manuscript:

API	Application Programming Interface
CECR	Content Element Coverage Rate
DPER	Data Portal Evaluation Rubric
DRCR	Data Record Completeness Rate
FCD	Floating Car Data
GIS	Geographic Information System
ITS	Intelligent Transportation System
LBV	Landesbetrieb Verkehr
MAE	Mean Absolute Error
RMSE	Root Mean Squared Error
SPS	Smart Parking System
TOCR	Temporal Occurrence Coverage Rate

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