



Review

Integration of Smart Pavement Data with Decision Support Systems: A Systematic Review

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Abstract: Nowadays, pavement management systems (PMS) are mainly based on monitoring processes that have been established for a long time, and strongly depend on acquired experience. However, with the emergence of smart technologies, such as internet of things and artificial intelligence, PMS could be improved by applying these new smart technologies to their decision support systems, not just by updating their data collection methodologies, but also their data analysis tools. The application of these smart technologies to the field of pavement monitoring and condition evaluation will undoubtedly contribute to more efficient, less costly, safer, and environmentally friendly methodologies. Thus, the main drive of the present work is to provide insight for the development of future decision support systems for smart pavement management by conducting a systematic literature review of the developed works that apply smart technologies to this field. The conclusions drawn from the analysis allowed for the identification of a series of future direction recommendations for researchers. In fact, future PMS should tend to be capable of collecting and analyzing data at different levels, both externally at the surface or inside the pavement, as well as to detect and predict all types of functional and structural flaws and defects.

Keywords: smart pavement; decision support systems; pavement management systems; smartphone; unmanned aerial vehicle (UAV); self-powered sensors; image processing; artificial intelligence



Citation: Amândio, M.; Parente, M.; Neves, J.; Fonseca, P. Integration of Smart Pavement Data with Decision Support Systems: A Systematic Review. *Buildings* **2021**, *11*, 579. <https://doi.org/10.3390/buildings11120579>

Academic Editor: Bjorn Birgisson

Received: 13 October 2021

Accepted: 19 November 2021

Published: 25 November 2021

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1. Introduction

The maintenance and rehabilitation of in-service pavements are pivotal activities of transportation engineering. The importance of maintaining functioning, comfortable and safe transportation networks reside in the fact that the economic and social growth of a country depends heavily on the health of its transportation network. Maintenance and rehabilitation (M&R) activities are usually planned based on the quality of the pavements, both at functional and structural levels.

Many countries and infrastructure agencies have their own pavement management system (PMS) to support decisions on when to intervene to maintain or rehabilitate the pavement of a segment of the infrastructure network. However, the state of the pavement quality of a network on which this PMS is based is still monitored by processes that have been established for a long time, and strongly depend on acquired experience.

The application of new smart technologies, such as internet of things (IoT), sensorization, and artificial intelligence (AI), has the potential to transform transportation engineering into a smarter and more efficient field, while simultaneously contributing to more sustainable development, meeting the goals established by the United Nations [1,2]. The PMS could be improved by applying these new smart technologies to their decision support systems, not just by updating their data collection methodologies, but also their data analysis tools. The application of these smart technologies to the field of pavement monitoring and condition evaluation will undoubtedly contribute to more efficient, less

costly, safer, and environmentally friendly methodologies and processes that will bring significant societal and economic benefits.

Smart pavement is a concept that is increasingly referenced in academic publications, though its definition is slightly sparse among researchers. Even though smart pavement is a broad concept, an advantage of these kinds of new, digital era pavements is their capacity to monitor their structural and functional health in real time by means of sensorization.

Even though in practice, infrastructure agencies are still dependent on conventional methods that are either costly or based on lengthy processes, the literature reveals that many researchers are exploring new approaches to detect and predict the state of a pavement by means of low-cost and easy-to-implement technologies. Thus, the aim of this paper is to carry out a comprehensive review of the approaches and methodologies which promote the development of smart pavement systems, with the capability of generating and analyzing data so as to provide the foundation for effective decision support systems (DSSs).

The remainder of the paper is organized as follows. Section 2 explores concepts such as smart pavement and how it can be integrated toward the improvement of the current PMS. In Section 3, the main research questions are presented, together with the methodology followed for the literature review, as well as a statistical analysis of the results. According to this literature review methodology, Sections 4 and 5 then detail the existing data collection and data analysis methods, respectively. Finally, conclusions are drawn in Section 6, followed by an analysis on future trends and recommendations.

2. The Role of Smart Technologies in Current Pavement Management Systems

PMSs can be considered decision support systems that aid infrastructure agencies in the planning of M&R actions to maintain a functional and safe network. The most important output of a PMS is the generation of an M&R action plan, which is achieved by applying decision support tools that usually take into consideration the minimization of costs of M&R actions to maintain an acceptable network condition. These decision support tools receive as input the present quality of the pavement and the financial resources available and output the M&R plan. However, the effectiveness and efficiency of these decisions made by the PMS highly depend on the quality of the input data that the decisions are made upon. In turn, the quality of the data depends on the considered method of collection and data analysis, which means that, for instance, a data collection method based on subjective criteria may compromise decision making. Thus, the type of adopted data collection and analysis methods not only influences the quality of the data, but can also improve the time and cost of the process of data collection and treatment [3,4].

Currently, the PMS in use by infrastructure agencies still depends on empirical methods of pavement condition evaluation and manual techniques of data collection. These agencies are held down by data collection methods that are either subjected to an engineer's experience-based evaluation or slow-moving automated processes that are only scheduled sporadically, due to the inconveniences and high cost normally associated with these methods. The most used methods of data collection, namely for surface distress evaluation, are visual inspections, either on foot (walking surveys) or by driving along the shoulder at lower speeds (riding surveys also known as windshield inspection). The ensuing data are translated into reports based on subjective evaluations, photos or videos and manual measurements taken during these inspections. For structural and roughness evaluations, the agencies usually own dedicated vehicles equipped with special sensors, such as inertial profilers, deflectometers, ground-penetrating radar, infrared thermal imaging, and laser technology. Although automatic, these methods take a significant amount of time, depend on costly equipment, and sometimes disturb the normal traffic flow. In general, issues arise not because of the lower efficiency of these methods to monitor the pavement condition, but because of the long periods between evaluations, reducing the efficiency of the whole monitoring system and potentially compromising the decision-making process. Thus, ample room for improvement exists in what concerns both data collection and analysis methods that comprise DSS for pavement management.

In the new industrial revolution—Industry 4.0—marked by the emergence of new technologies capable of automating and optimizing processes, the “smart” concept has gained increasing attention. In both industry and academic worlds, the concepts of smart city and smart home are examples of well-established and advertised terms. However, the concept of smart road or smart pavement is not as well defined or disseminated. Some authors considered that smart road includes four main features [5,6]. According to Pompigna and Mauro [6], smart roads should be capable of the following: learn with and assess itself (by monitoring its conditions in real time); adapt to the circumstances of the road (for instance, cracking or icing); interact with other intelligent devices (such as vehicles) and connect to databases of maintenance systems through a communication system; and feed themselves by supplying green energy. Throughout this paper, the term smart pavement was adopted to drive the focus to smart technologies applied to the pavement in view of automating its monitoring, as opposed to other smart road components and features, such as those related to energy and communication for instance [5].

Ultimately, the decisions made by these systems are not just affected by the chosen methods of data collection, but by the data analysis methods as well. Many researchers have focused on the analysis of smart data collection methods applied to pavement monitoring, such as unmanned aerial vehicles (UAV) [7], probe vehicles (basically vehicles equipped with sensors) [8], smartphones [9], and embedded sensors in the pavement [10–12]. Many other state-of-the-art works that explore data analysis methods as well have mainly focused on just one type of functional distress (such as cracking or surface irregularity measurement) [7,8,13] or in structural evaluation [11]. Yet not many surveys make the bridge between smart data collection methods and data analysis methods also based on new intelligent techniques, which are suited to be a part of DSS for smart pavements.

With the possibility of gathering a significant amount of varied data (including real-time data) it becomes advantageous to use AI techniques, such as machine learning (ML), to extract knowledge from this information, allowing for the detection and prediction of pavement conditions. Image processing is also increasingly adopted to detect various types of surface distresses. The work by Peraka and Biligiri [4] evidenced the significance of the link between both data collection and data analysis methods as decision support tools dedicated to pavement management. However, their analysis of the current state-of-the-art focuses solely on the monitoring of the pavement’s functional condition (i.e., detection and prediction of surface distresses or estimation of roughness indicators), while disregarding the potential of an in-depth analysis of a broader DSS concept capable of taking into consideration the developed tools for both functional and structural monitoring of pavements.

Therefore, future DSSs for pavement management would benefit from integrating smart data collection and data analysis techniques for both functional and structural evaluations. This integrated approach could result in a decrease in both cost and resource usage associated with the maintenance and monitoring plans of infrastructure agencies without significant reductions in efficiency when compared with current systems and techniques in use. Figure 1 depicts a DSS as such, including the currently available smart data collection methods and the levels of analysis that were studied for both functional and structural pavement characteristics.

Thus, this paper aims to fill this literature gap, covering both data collection methods, analysis techniques and decision support tools applied to the pavement management and maintenance field that can be found in the literature. Simultaneously, a distinction is delineated between which tools and methods are applicable to the two most crucial pavement condition levels: functional and structural. The main drive of the present work is to provide insight for the development of future decision support systems for smart pavement management. Indeed, future DSSs need to be capable of collecting and analyzing data at different levels, both externally at the surface or inside the pavement, as well as detecting and predicting all types of functional and structural flaws and defects. The narrative followed by this work is, thus, represented in Figure 1, which depicts the two

main components of a DSS and how they fit in a smart pavement environment: data collection methods, and data analysis and decision support tools.

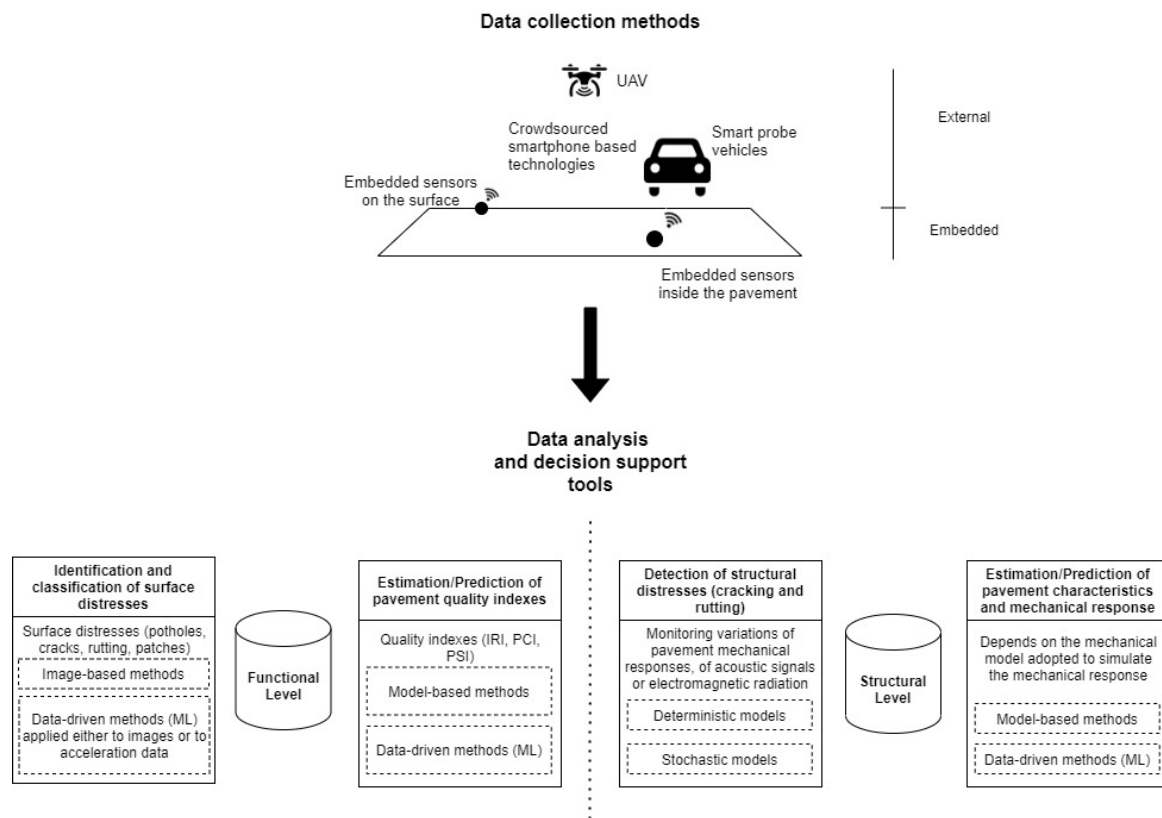


Figure 1. Decision support system for smart pavements.

3. Research Methodology

Research Questions

The aim of this work is to identify and assess the new smart technologies applied to pavements that can provide the foundation for a more efficient and effective DSS comprised of data collection and analysis modules for the monitoring of the pavement state. Hence, three research questions (RQ) were identified as guidelines to the research approach, namely, the following:

- RQ1—What smart technologies are being utilized to monitor pavement condition? (Section 4)
- RQ2—Which methods of data processing and analysis are most commonly applied to the collected data and which ones have shown greater efficiency? (Section 5)
- RQ3—Are there any decision support tools that integrate both data collection and data analysis methods?
- RQ4—Are there any PMS capable of simultaneously monitoring both structural and functional conditions of pavements?

The research methodology implemented in this review is summarized in Table 1 and divided into three phases. In order to identify both the DSSs that have already been developed and simultaneously the works mainly based on data collection or data analysis methods, the first phase consisted of a wide search with broad keywords, such as “smart”, “pavements”, “decision support system”, “monitoring” and “management”. Words such as “road”, “transportation” and “infrastructure” were not considered to avoid works based on mobility, automated and connected vehicles, or monitoring of other type of infrastructures. From this first attempt, a poll of 1969 papers from peer-reviewed journals, reviews and conferences papers were obtained. These data were surveyed in September

2021 in referenced scientific databases, namely Elsevier Scopus, Science Direct, Springerlink Journals, Taylor&Francis online, IEEE Xplore and Google Scholar. Common boundaries were taken into account throughout this first phase to restrict the search, shown as follows:

- This review focuses on peer-reviewed scientific journals, conferences, and proceedings papers.
- In spite of the fact that the first papers that resulted from the query of the first phase of the research date back to the 1990s, the period considered for the search was limited to the period between 2015 and 2021, due to a bigger manifestation of relevant papers in the past 5 years.

Table 1. Literature review phases.

Phase	No. of Papers	Methodology
1	1992	Search for peer-reviewed journal articles, proceedings and conference papers in the most relevant scientific databases with the following combination of keywords: “smart” AND “pavement” AND (“decision support system” OR “monitoring” OR “management”)
2	110	Title and keyword filtering and abstract filtering
3	55	Content analysis + references cited in selected papers
Total		

This first poll of papers then went through an analysis of significance, firstly in function of their title, followed by an assessment of the abstract. This allowed the literature review process to filter a significant amount of works from areas that were beyond the topic of this paper but were still output by the keyword search, such as mobility and logistics, or smart vehicle communication and automation. Then, the most relevant papers resulting from that selection went through a more thorough content analysis. This process of selection was carried out by two researchers by following the previously stated rules and the concept of DSS for smart pavements exposed in the preceding section. Between each phase, the researchers discussed and combined their findings and selected papers. It is important to remark that, while analyzing the content of the selected papers, cited references were also considered a secondary source for which the corresponding numbers are depicted in Table 1. These additional references were also subjected to the aforementioned boundaries concerning the publication type and year of publication.

The content of the papers was assessed by conducting a descriptive analysis on the distribution across the considered time interval, the distribution by category, and then a geographical distribution by continent.

Figures 2 and 3 represent the distribution of publications throughout the considered time interval for embedded and external methods regarding data collection and functional and structural analysis considering data analysis methods. It is important to note that not all papers explore both data collection and data analysis methods in the same work. Therefore, the number of articles in both figures slightly differ, as some works figure in both graphs, while others are only represented in one of them. By analyzing both distributions simultaneously, we can infer their similarity and growing trend. Even though the application of smart technologies to pavement maintenance was already explored widely in the past, including earlier than 2015, these distributions still show a significant growth concerning the interest on the topic at hand in the past 5 years, peaking around 2020 with around 60% of the publications occurring after 2019. Another aspect of note is concerned with the fact that, for 2021, a significant amount of works was already published up until September 2021, demonstrating the increasing interest in these topics.

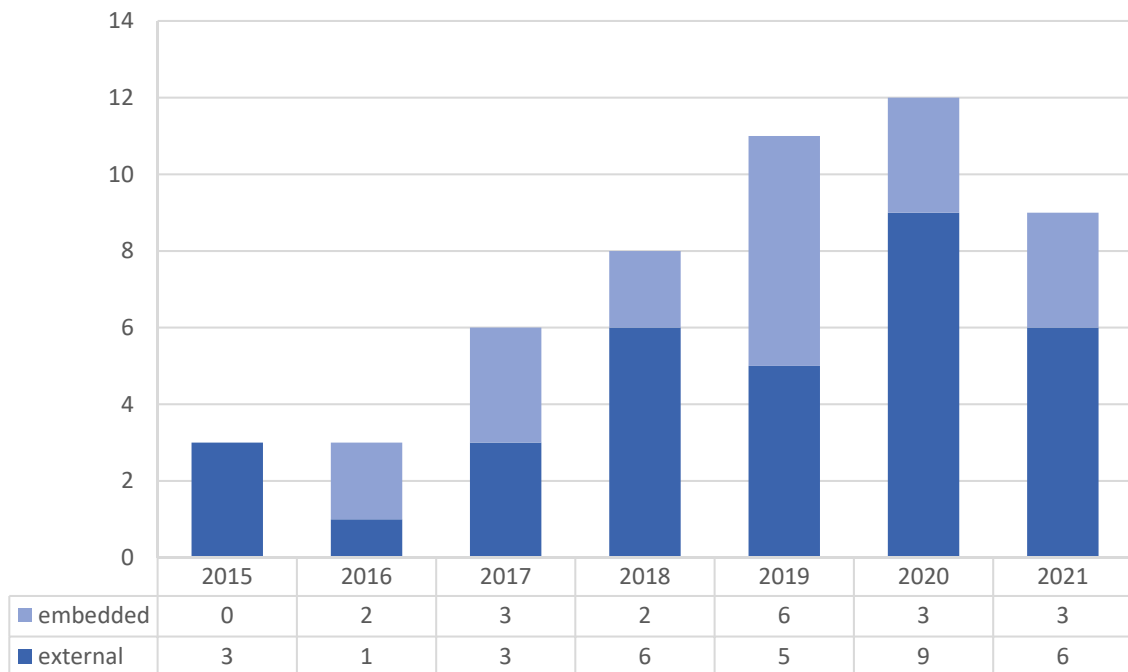


Figure 2. Distribution of data collection methods through 2015–2021.

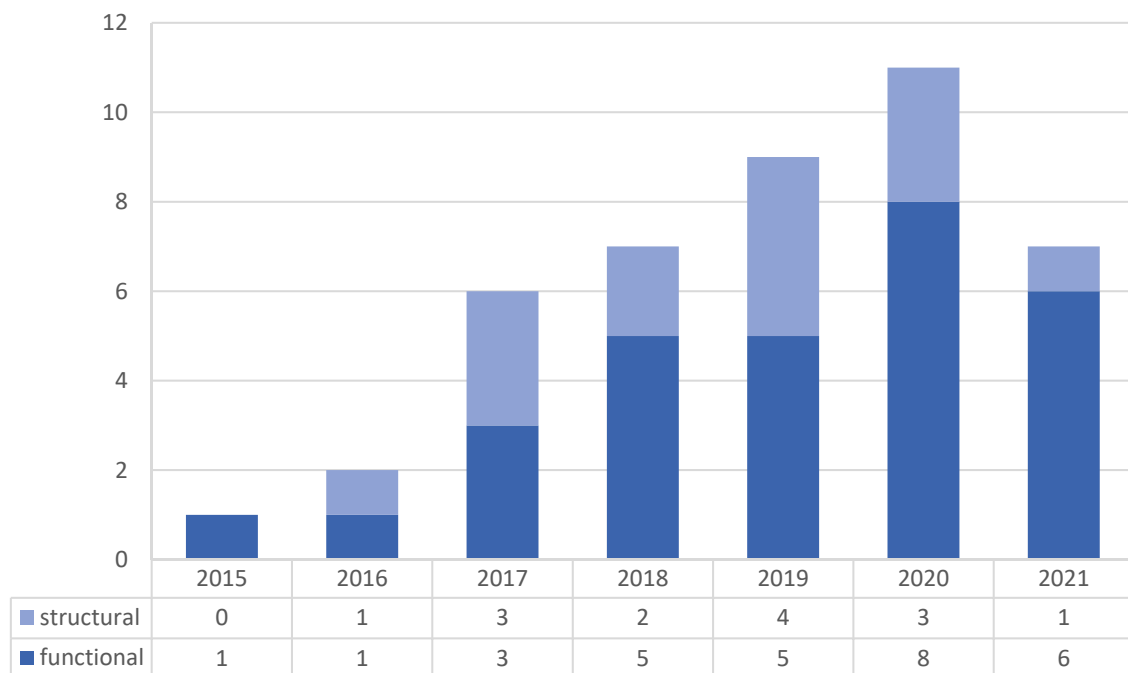


Figure 3. Distribution of data analysis methods through 2015–2021.

Regarding the geographical distribution represented in Figure 4, the continents that most contributed to these topics for the past five years correspond to Asia, followed by Europe and only then by North America. The biggest contributors in these top three continents are China, U.S.A., and Italy.

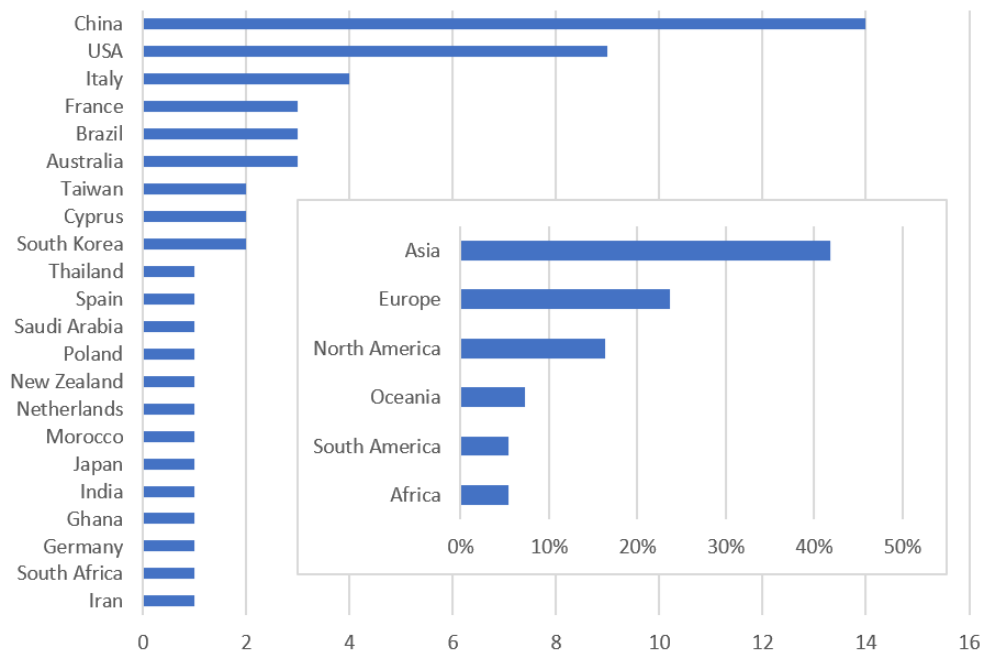


Figure 4. Distribution of published documents by country and by continent.

4. Data Collection Methods

4.1. General Aspects

Bearing in mind the first research question of this analysis (RQ1), Table 2 categorizes the works that explore smart data collection methods and monitoring technologies that could integrate a DSS for smart pavement management. Most of these works focus only in one type of data collection, either external or embedded.

Table 2. Classification of research developments by data collection methods.

Type	Method	Types of Sensors	References
External	Smartphone	Accelerometer, GPS, camera, gyroscope, microphone	Wu et al., 2015 [14]; Seraj et al., 2016 [15]; Aleadelat et al., 2017 [16]; Zhao et al., 2017 [17]; Hadjidemetriou et al., 2018 [18]; Meng et al., 2018 [19]; Souza et al., 2018 [20]; Zeng et al., 2018 [21]; Chuang et al., 2019 [22]; Alavi et al., 2019 [9] *; Nunes et al., 2019 [23]; Agebure et al., 2020 [24]; Patra et al., 2021 [25]; Shtayat et al., 2021 [26]; Staniek et al., 2021 [27]
	Smart probe vehicle	Camera, laserscan, accelerometer, microphone, GPR	Wang et al., 2015 [28]; Zhang et al., 2017 [29]; Chatterjee et al., 2018 [30]; Hadjidemetriou et al., 2018 [18]; Chen et al., 2019 [31]; Wu et al., 2019 [32]; Alfarraj et al., 2020 [33]; Alsharahi et al., 2020 [34]; Nguyen et al., 2020 [35]; Park et al., 2021 [36]; Rateke et al., 2021 [37]
	UAV	Camera, laserscan, GPS	Mettas et al., 2015 [38]; Outay et al., 2020 [7] *; Chansamorn et al., 2020 [39]; Roberts et al., 2020 [40]; Silva et al., 2020 [41]

Table 2. Cont.

Type	Method	Types of Sensors	References
Embedded	On the pavement surface	Microphone, piezoelectric, optical fiber	Fedele et al., 2017 [42]; Hasni et al., 2017 [43]; Bi et al., 2019 [44]; Cafiso et al., 2020 [45]
	Inside the pavement	Optical fiber, piezoelectric, geophones, gauges (strain, stress, temperature, moisture)	Alavi et al., 2016 [46]; Kodippily et al., 2016 [47]; Lenglet et al., 2017 [48]; Ma et al., 2018 [49]; Wang et al., 2018 [50]; Bahrani et al., 2019 [51]; Duong et al., 2019 [52]; Ji et al., 2019 [53]; Ma et al., 2019 [54]; Zhao et al., 2019 [55]; Graziano et al., 2020 [11] *; Liao et al., 2020 [56]; Abejide et al., 2021 [57]
	Smart Composites	Self-sensing materials (such as piezoresistive and conductive materials)	Dong et al., 2020 [58]; Birgin et al., 2021 [59]

* review paper.

Smartphone-based approaches seem to be the most explored, due to the popularity of these devices, together with their widespread availability and ease of use. Regarding UAV applications, despite the fact that fewer papers were retrieved on this specific topic, the survey includes a comprehensive review paper analyzing the applications of UAV to road safety, traffic and highway management [7]. According to the classification shown in Table 2 and supported by Figure 1, the topic which still seems to be the least explored is related to the use of embedded sensors on the pavement surface.

Regarding external data collection methods, these are often associated with a type of dynamic monitoring featuring a long-span capacity of collecting data associated with extensive network sections. Most of these methods leverage on vehicles equipped with sensors being the most common among cars and UAVs. Sensors can either be installed and mounted on these vehicles or included in smartphones as built-in sensors. Generally, these external methods focus either on the detection of surface distresses (such as potholes and cracks) through the analysis of acceleration data, image processing and/or acoustic signals, or on the evaluation of the surface condition by the estimation of pavement condition and performance indexes also by means of acceleration.

Taking smart wireless sensor networks into account as embedded methods, this type is usually associated with a local and static pavement structural health monitoring. Conventional non-destructive methods (such as falling weight deflectometer—FWD) that seek to measure and evaluate pavement structural health mainly reflect the distress conditions of the pavement surface, rather than the internal stress/strain state and structural degradation of the pavement, as they are unable to detect micro-damage and track its development. This comprises one of the main drives for the study and implementation of embedded smart sensor networks. The latter consist of a set of sensors, called nodes, that usually are integrated into a new structure during construction, or alternatively integrated at the surface of an already existing one to monitor a particular event or measure a certain parameter continuously in real time [11].

4.2. External Methods

4.2.1. Smart Probe Vehicles

In this analysis, this category considered vehicles equipped mainly with low-cost sensors and used in frequent monitoring actions, as opposed to the conventional vehicles used by infrastructure agencies, equipped with high-accuracy and expensive sensors which monitor the network periodically. The works that resorted to these smart probe

vehicles focus either on image-based collection methods [28–30,32,36], or accelerometer, microphones and global positioning system (GPS) sensors for international roughness index (IRI) estimation and crack detection [28,31].

Wang et al. [28] proposed a multi-modal sensor system that can be installed in any type of vehicle and is capable of collecting both surface- and subsurface-related information by means of several types of sensors, ranging from acoustic, to optical, electromagnetic and GPS. The developed system was presented as a non-intrusive, affordable solution that does not require experts to conduct the data collection. The acoustic sensors (microphones) were used to quantify the “macrotexture depth” of the pavement (which is an indicator of roughness). A dynamic tire pressure sensor (DTPS) and an accelerometer were used to estimate IRI. Cameras were adopted to take images of the pavement for crack detection and identification. Lastly, ground-penetrating radar (GPR) was used to assess the asphalt thickness and electromagnetic properties. GPR technology is also sometimes used to detect the presence of cracks and cavities [34].

While both Zhang et al. [29] and Chatterjee et al. [30] used a system based on cameras and GPS for image processing to detect surface cracks on the pavement [33,37], Chen et al. [31] resorted instead to the collection of acceleration and audio signals to detect cracks. Acceleration data were collected by both a smartphone built-in sensor together with an accelerometer mounted on a car wheel frame, and an audio signal was collected by a voice recorder. At the same time, pavement images were obtained by a camera mounted on the car, which were then used as a ground truth for the estimation model. Nguyen et al. [35] developed a system that also collected acceleration data through an IoT device placed outside the vehicle, and which also integrated a gyroscope and GPS signal receivers. The recorded variations of vibration were then used in a visualization tool that represented the quality of the network surface.

Despite already being used for surface distress detection, laser scanning technology can also be considered a smart technology capable of supporting automation, and thus simplify the process of collecting point cloud information to build a tri-dimensional (3D) model of the pavement surface [32].

4.2.2. Smartphone-Based Methods

Current smartphones typically include built-in sensors, such as accelerometers, gyroscopes, and GPS, besides microphones and cameras with increasing quality, thus comprising useful tools to monitor pavement performance and surface condition. Many researchers have studied the application of smartphones to monitor pavement condition since this method can present itself as a low-cost real-time data collection alternative to current monitoring methods used by infrastructure agencies [9]. A smartphone-based method is not only capable of gathering reliable data, but it also facilitates real-time monitoring of the entire network. Methods of data collection based on smartphone accelerometer and GPS readings are the most common. Most studies of smartphone-based data collection methods either focus on pavement performance evaluation and estimation of pavement quality indexes [16,17,19–21], or on anomaly detection [15,18], with a prominent focus on pothole identification. While built-in accelerometer sensors are the most used in smartphone-based systems [14–16,20,22–24,26,27], there are systems that use cameras [18,25] and microphones as data collection methods.

Aladelat et al. [16] resorted to a smartphone accelerometer and GPS to evaluate pavement condition through the estimation of present serviceability index (PSI). More precisely, they proved that the variance of the acceleration data obtained by smartphones could work very effectively as independent variables to estimate PSI. In turn, PSI depends on indicators, such as international roughness index (IRI) [17,19], pavement condition index (PCI), and pavement rutting as explanatory variables. The difference between the predicted and the actual PSI values was not statistically different, but it is a model that is highly dependent on the smartphone used and type of vehicle.

Souza et al. [20] also resorted to smartphone acceleration data and GPS to assess pavement quality. To achieve this, the authors defined their own pavement condition classification (good, average, fair, poor and obstacle) according to the degree of comfort or discomfort experienced by a road user.

Bearing in mind the methods focused on anomaly detection, Seraj et al. [15] adopted smartphone GPS and inertial sensors (accelerometer and gyroscope) to detect pavement anomalies, which are classified in groups, such as transversal, mild and severe road anomalies. Transversal anomalies included intentional road elements, such as speed bumps and joints. Mild anomalies included crocodile cracks, patched roads, tree roots, sunken manholes, or raveling. Lastly, severe anomalies ranged from potholes to severe road deteriorations.

Considering the pervasiveness of smartphones, some studies focused on the conceptualization of crowdsourcing base monitoring systems. Chuang et al. [22] proposed and conceptualized a participatory smartphone-based system to evaluate pavement performance through the analysis of both vertical and lateral acceleration retrieved from smartphone accelerometers. Instead of attempting to estimate IRI, this work established a novel pavement performance index (PPI) that could provide infrastructure agencies with information regarding the network stretches with a worse performance, on which IRI estimation procedures can then be carried out by equipped vehicles. Rather than replacing IRI as an assessing indicator, this novel index intended to assess and label road anomalies to optimize labor- and time-associated costs in a network.

4.2.3. Unmanned Aerial Vehicles

As for data collection methods resorting to UAV, these have mainly focused on pavement distress recognition obtained by image processing, with cracks and potholes being the most common detected distresses [7]. To realize a UAV-based monitoring system, the most employed equipment for the detection of surface distresses is either high-resolution cameras [38,40,41] or light detection and ranging (LiDAR) systems, which generate point cloud data [39]. By resorting to high-resolution cameras, surface distresses can either be detected by analyzing 2D images [41], or by generating 3D models of the pavement surface by applying structure-from-motion (SfM) techniques [40].

Chansamorn et al. [39] tested the feasibility of a low-cost LiDAR-equipped UAV system to monitor road surface conditions. The effect of elevation and tilt angle in LiDAR-equipped UAV measurements was thoroughly explored to define the flight parameters that minimize measurements failures.

With respect to some barriers concerning the application of UAV, Outay et al. [7] identified the most critical restrictions to the use of drones, including those figuring in airspace regulations as dictated by each nation's space monitoring agencies. Besides these, restrictions at the operation level of drones speculate that these can only be used under the visual line of sight of the operator. Other restrictions are related to weight, equipment (sensors and cameras), day-only operations, the need for professional training and certification to operate these UAV, registration of the drone, and prior permission for using the air space.

4.3. Embedded Methods

In this analysis, a distinction was made between sensors embedded into the pavement [46–52] and those applied directly on the pavement surface [42–44]. These monitoring systems focus either on the monitoring of the propagation of concealed cracks [42,43,46,48], or on the estimation of structural capacity [47,49–52,57] influenced by pavement parameters that can be measured by specific sensors, such as strain, temperature, or moisture gauges. Nevertheless, embedded methods are not exclusive to the monitoring of structural condition, as these systems have also been used to monitor functional aspects. In this line of work, Bi et al. [44] developed an optical fiber-based monitoring system for tracking the

water membrane thickness on the pavement surface, which has a relevant impact on user safety as a consequence of potentially affecting the pavement skid resistance.

Ma et al. [49,54] presented a framework to estimate the modulus of asphalt layers by monitoring stress and strain responses measured by a fiber optic sensor (fiber Bragg grating sensors—FBG). This framework was tested in the field, and the sensors were embedded at the bottom of the second asphalt layer. On the other hand, Wang et al. [50] presented a sensing technique based on the simultaneous application of two types of optical fiber sensors: FBG for point and local detection with high precision, and Brillouin optical fiber for distributed monitoring with relatively low precision. While the former was able to detect local deformation, local cracks and shrinkage, the latter was employed to measure the global mechanical properties and global deformation. When it comes to rigid pavements, optical fiber sensors were also used to monitor thermal curling of concrete pavement slabs [56] and concrete pavement support conditions [55]. Since one of the main concerns with embedded wireless sensors regards their energy supply, piezoelectric transducers are seen as a good alternative for continuous pavement health monitoring on account of the capacity of both damage diagnosis, and for supplying power to themselves from traffic loads. Alavi et al. [46] focused on finding a correlation between the distribution of strain measured by piezoelectric transducers and damage progression, such as bottom-up crack propagation. It was found that damage progression can be considered a function of probability density function parameters obtained from the strain distribution. Correspondingly, Ji et al. [53] conceived a self-powered damage-detection aggregate (SPA) comprising a piezoelectric vibrator. The encapsulation thickness and vibrator size were tuned to obtain the best results in the detection of concealed cracks. Contrary to the application of piezoelectric transducers to measure strain by Alavi et al. [46], Ji et al. [53] resorted to the principle of acoustic wave attenuation to detect and measure cracks width. When a SPA driver is excited, it generates an acoustic wave which propagates through the pavement until it reaches an SPA receiver. In the presence of concealed cracks, the received signal, and the coefficient of the acoustic wave attenuation change, the latter is reduced as the crack width increases.

As mentioned, one of the drawbacks of embedded sensors is that they are either installed during construction of new pavements or during rehabilitation interventions. Conversely, the method proposed by Hasni et al. [43] accounted for the application of sensors on existing pavements by placing the sensors on the surface instead of inside the pavement layers. The self-powered wireless surface sensing approach made use of piezoelectric transducers to detect bottom-up cracking. Another work that explored a method for detection of cracks inside the pavement was developed by Fedele et al. [42] and Cafiso et al. [45], which resorted to microphones placed on the pavement surface to record its vibro-acoustic signature. Since the propagation of both vibration and sound is, among others, a function of the properties of the material, this method is based on the hypothesis that, in the presence of cracks, the stiffness of the pavement decreases, resulting in a reduction in the wave transmission capacity of the material.

New developments have also addressed the implementation of self-sensing smart composites comprised of the inclusion of piezoresistive and conductive materials in the formulation of new pavements [58,59]. Contrary to embedded sensors inside the pavement, this approach presents itself as a solution to some of its drawbacks, such as energy supply, sensor durability and possible impacts in the performance of the pavement itself. Obvious drawbacks are concerned with the fact that these novel materials must be added to the materials during construction, which, besides the increased cost and quality control requirements, may in some cases modify the mechanical behavior of the final pavement.

5. Data Analysis and Decision Support Tools

5.1. General Aspects

When it comes to evaluating pavement condition data, this topic is usually subdivided into functional and structural condition evaluation. While the former is the more common and aims to define the quality of the pavement surface regarding the user's comfort and

safety, structural evaluation seeks to define the mechanical response of the pavement, taking into account the effects of traffic and climatic conditions [60]. Typically, most PMS initially focus on the functional condition assessment of pavements, while the structural evaluation is carried out only when required. Conversely, the capability of smart pavements to constantly monitor both functional and structural aspects can present itself as a solution for this problem.

Following the survey of data collection methods in the previous section, the natural follow-up topic comprised the study of the most efficient processing and analysis methods applied to the data collected by the methodologies in Section 4 (RQ2). To achieve this goal, a survey of data analysis methods was carried out by assessing existing developments pertaining to smart decision support tools capable of advising the infrastructure agencies on the condition of the pavement, both at a structural and at a functional level. Table 3 identifies some of the works that were developed in this regard and divides them into functional and structural analyses.

Table 3. Classification of research developments by data analysis methods.

Type	Focus	Method	References
Functional	Identification and classification of surface distresses	Image-based/Laser scanning-based methods	Wang et al., 2015 [28]; Zhang et al., 2017 [29]; Sarker et al., 2019 [61]; Roberts et al., 2020 [40]
		Data-driven methods	Seraj et al., 2016 [15]; Agebure et al., 2020 [24]
		Image-based + Data-driven methods	Chatterjee et al., 2018 [30]; Hadjidemetriou et al., 2018 [18]; Weng et al., 2019 [62]; Wu et al., 2019 [32]; Alfarraj et al., 2020 [33]; Chen et al., 2020 [63]; Chen et al., 2020 [64]; Guo et al., 2020 [65]; Silva et al., 2020 [41]; Kim et al., 2021 [66]; Park et al., 2021 [36]; Patra et al., 2021 [25]; Rateke et al., 2021 [37]; Shahbazi et al., 2021 [67]
	Estimation of pavement quality indexes (IRI, PCI and others)	Model-based methods	Aleadelat et al., 2017 [16]; Zhao et al., 2017 [17]; Meng et al., 2018 [19]; Zeng et al., 2018 [21]; Chuang et al., 2019 [22]; Staniek et al., 2021 [27]
		Data-driven methods	Souza et al., 2018 [20]; Nunes et al., 2019 [23]; Majidifard et al., 2020 [68]
Structural	Detection of fatigue cracking and micro cracks	Deterministic model	Fedele et al., 2017 [42]; Lenglet et al., 2017 [48]; Wang et al., 2018 [50]; Ji et al., 2019 [53]
		Stochastic model	Alavi et al., 2016 [46]; Hasni et al., 2017 [43]
	Estimation of pavement elastic modulus and structural capacity; prediction of mechanical response	Model-based method (deterministic)	Ma et al., 2018 [49]; Bahrani et al., 2019 [51]; Duong et al., 2019 [52]; Ma et al., 2019 [54]; Alsharahi et al., 2020 [34]; Cafiso et al., 2020 [45]; Liao et al., 2020 [56]; Abejide et al., 2021 [57]
		Data-driven method (stochastic)	Ma et al., 2019 [54]; Zhao et al., 2019 [55]

One of the focal points of functional analysis is the evaluation of the pavement surface quality. Since this analysis is usually carried out in a two-fold action, starting with the identification of surface distresses followed by the determination of quality indexes, the functional category was sub-divided into a second level. This sub-division aimed to distinguish the data analysis methods that focused on the identification and classification of surface distresses, such as superficial cracks [28–30,33,40,62–67], potholes [25,32,36], patches [18], and others [37,41], and the estimation of pavement quality indexes, such as IRI [17,19], PCI [16] and other indexes proposed by some researchers [20,22,23,27,68]. These sub-categories were, in turn, divided into the type of adopted approach, either image processing or data-driven models for the case of identification and classification of surface distresses, and model-driven or data-driven for the estimation of pavement quality indexes.

Regarding the structural category, it was also divided into two distinct sub-categories related to the main focus of the systems under analysis. The works were divided into those that focused on the identification of fatigue cracking [42,43,46,48,50,53], most commonly bottom-up cracks, and the estimation of pavement layers' elastic modulus and the prediction of mechanical response [34,45,49,51,52,54–56], which are intrinsically related.

5.2. Functional Evaluation

5.2.1. Identification and Classification of Surface Distresses

The two most commonly used data types for the identification and classification of surface distresses are image and acceleration data. Concurrently, the most common methods for the analysis of the subsequent data are image processing techniques and data-driven models, applied individually or in tandem with each other.

Image processing methods and techniques are mostly used for (but not limited to) the detection of surface distresses, such as cracks and rutting [28–30,33,37,41,62–64,66–68], potholes [25,32,36,37,41,68] and patches [18,37]. As mentioned in the previous section, image-based collection methods, which usually resort to high resolution cameras, have been widely studied. The images captured by those cameras can be processed as two-dimensional (2D) images for distress detection [18,25,30,32,33,36,37,41,62–66,68], or used to generate 3D models of the pavement, aiming to assess the surface roughness [61], deformation levels [40] or patch depth [32]. A common step among image processing methods is image segmentation, which involves dividing the image in smaller sections based on certain features and characteristics, culminating in the isolation of the pavement distress that is intended to be detected.

Zhang et al. [29] proposed a crack detection system based on an adaptive threshold image segmentation method and a region growing algorithm applied to grayscale pavement images. This methodology takes into account crack features, such as spatial distribution, intensity, statistical, geometry and orientation to separate crack pixels from the background. The dependency on the grayscale intensity of pixels had a direct limitation when it came to detect cracks that do not have an obvious grayscale intensity difference when compared with their surrounding area. Therefore, the authors suggested the combination of depth information with intensity features so as to detect cracks when the difference in the level of intensity is not significant.

When it comes to generating 3D models to assess the road surface conditions, these can be generated from 2D images taken from the field by applying SfM modeling techniques, while simultaneously using image segmentation to isolate the pavement distresses. In this context, Roberts et al. [40] used drone images to generate a 3D model of pavement sections in order to monitor and analyze pavement surface conditions. In this study, the condition of the pavement for each analyzed section was determined by a statistical metric representing the average level of distress of that section. This metric was obtained by using a statistical analysis of the deviations between the model and a reference plane. The authors also evidenced the relevance of their process to aid road managers in deciding an intervention plan based on the section surface condition translated from the value of the used metric.

For the purpose of distress identification and classification, the most used methods typically integrate image-based techniques with data-driven models. This kind of process usually starts with image processing and segmentation to extract a set of features, which are then subsequently used to train machine learning models. Convolutional neural networks (CNN) are well-known machine learning methods usually applied in image detection systems, such as these ones. Hence, the majority of the systems described herein applied variations of CNN [25,32,33,36,63–67], such as YOLO (you only look once) [41,68] or U-NET [37,68] architectures. Apart from CNN, though not as common, random forest [18] and support vector machine (SVM) [30,62] machine learning methods were also successfully used for distress detection.

Hadjidemetriou et al. [18] focused their work on the detection and quantification of patches by applying a SVM classification model to video frames. In this study, each frame was firstly divided in blocks of 20×20 pixels, which were classified as patch or no-patch blocks by the SVM model with an accuracy of 87.3%. Subsequently, this block classification was used to categorize each frame as including patches or not, which in turn was achieved by defining a threshold of connected patch blocks.

Weng et al. [62] proposed a segment-based method to measure crack width. The process behind the developed method can be divided in five main steps. First, a crack edge confidence map was obtained by applying random forest machine learning based on features such as the commonly used grayscale intensity, coupled with a newly identified feature: the curved structure of cracks. This new feature was important to identify hairline cracks, whose intensity is not enough to distinguish them from the background with certainty. Based on the crack edge confidence map, the crack skeleton, which characterizes the propagation of the crack, was extracted, broken down into individual crack curves and then partitioned into crack segments whenever the crack curvature exceeded a defined threshold. Lastly, the crack length can be obtained by adding the crack segment lengths. Since the crack width was considered to be constant for each segment, the final width corresponded to the distance between the two crack edges of a segment.

The system developed by Rateke et al. [37] was capable of assessing several characteristics of a road, combining the identification of surface type (asphalt, paved and unpaved) with the detection of surface distresses, such as potholes, cracks, and patches, among others. In order to attain accurate detections of both pavement surface types and surface distresses, the approach consisted of training a CNN model to perform semantic segmentation by applying a U-Net architecture. Firstly, the model was trained without the use of weights in the classes to easily identify the surface type. Secondly, this model was used as pre-training for a second model with the application of balanced weights. The second model produced better results in detecting road defects. However, this method overly simplified the distress classification since it leaned on the assumption that any distress that does not fall within the classification of potholes and patches must be classified as cracks, which may not always necessarily be true.

Wu et al. [32] proposed a new algorithm for pothole detection which integrates 2D and 3D image processing techniques. First, a semantic segmentation CNN model was applied to 2D images to extract candidate potholes which were then generated into 3D models via point cloud information obtained from a laser scanner. Then, the candidate potholes were verified by a depth analysis to separate the real potholes from the patches by following a threshold methodology.

Despite the fact that image-based processing is the most employed technique used for surface distress detection, acceleration data are also used to detect a group of more limited anomalies (mainly potholes and bumps) by applying data-driven models to classify the vibration variations of a moving vehicle. Acceleration-based detection systems usually encompass signal processing and analysis phases, followed by feature extraction to train and test machine learning models. The signal processing and analysis consist of several denoising techniques, such as high-pass filters, demodulation, windowing, frequency domain, and wavelet transformation to smooth the signal and reduce the effects of speed [15],

collection device setup (in case of smartphones the placing is important), and vehicle dynamics (suspension effect).

Notwithstanding the main purpose described in this section of surface distresses detection, acceleration-based data-driven models can also be applied to classify the road type [24]. Thus, Agebure et al. [24] proposed a three-tier architecture capable of both detection and classification of anomalies and road type (paved or unpaved) by applying a novel neural network technique (spiking neural network) to statistical features extracted from smartphone built-in accelerometers.

5.2.2. Estimation of Pavement Quality Indexes

The most used pavement quality indexes in PMS are the international roughness index (IRI), pavement condition index (PCI) and present serviceability index (PSI). The IRI determines the smoothness of the pavement surface, and it is determined by using a quarter-car model to simulate vehicle dynamic response in order to obtain the road profile. While the PCI is a quality rating ranging from 0 (worst) to 100 (best) and it is obtained based on distresses observed during walking or riding surveys, the PSI, which ranges from 0 (very poor condition) to 5 (very good condition), is determined by a set of equations that are derived from the user perceptions and ratings for the present serviceability of the pavement. For the estimation of pavement quality indexes, acceleration is the most used data type, though image-based methods can also contribute to determine quality indexes since these usually depend on the frequency and severity of the surface anomalies detected by the latter methods. While model-driven systems attempted to estimate existent pavement quality indexes, such as IRI [17,19] and PCI [16], data-driven models focused on classifying the state of the surface into qualitative groups [20,23]. Concurrently, most model-driven systems resort to regression analysis [16,17,19], while data-driven resort to machine learning models, such as SVM [20] and random forest [23].

Acceleration data can be significantly volatile depending on the speed of the vehicle during collection. To tackle this, data were sometimes collected at pre-defined speeds, excluding any data collected outside of those pre-defined ranges during signal/data processing phase [16]. On the other hand, some systems considered the speed as an independent variable, attempting to compensate for vehicle acceleration and deceleration during collection phase [17,19]. Many of these studies tested their systems only on one single vehicle with specific characteristics [16,21]. However, novel solutions comprising the implementation of smartphone-based estimation systems on any type of vehicle and with different setups have been studied by considering a participatory, crowdsourcing solution. Those solutions must account for the variability of different vehicle dynamics, as well as for the installation setup, which are two additional variables that need to be considered besides speed dependency.

In this context, the most commonly adopted index, IRI, was obtained by applying the quarter car model, which depends on the dynamics of the vehicle. However, in a participatory system, the uncertainty in the vehicle response needs to be addressed. In this line, Zhao et al. [17] developed a two-step IRI estimation system based on the variation of the collected acceleration with a smartphone. Firstly, transfer functions were used to convert the root mean squared (RMS) value of the measured acceleration by considering the identified vehicle model to the RMS acceleration of the sprung mass of standard quarter car. The obtained RMS, which already reflects the vehicle pitching motions and smartphone installation setup, was then used to estimate IRI by means of linear regression. Zeng et al. [21] also considered that RMS showed a good correlation with IRI, and ended up performing a sample size analysis to determine how many trips would be needed to reach a robust estimate of IRI for a determined pavement section.

Another commonly used index, PSI, describes the pavement functional condition with respect to riding quality, which depends on the estimation of other indexes, such as IRI, PCI and rutting [16]. In fact, Aleadelat et al. [16] adopted regression analyses on smartphone acceleration data to determine PSI values. Signal processing includes both median and

average filters to smoothen the smartphone-acquired signal. Whereas previous systems only based their estimations on the vertical component of acceleration, Chuang et al. [22] considered both vertical and lateral acceleration to estimate PPI based on the perception of riding comfort. According to the authors, by considering both acceleration components, the need for having a predefined acceleration threshold to identify anomalies is avoided. Instead, the thresholds are assigned adaptively to a certain vehicle under different velocity since this is positively correlated with the amplitude of the acceleration.

Regarding data-driven models, Asfalt [20] and Streetcheck [23] focused on the evaluation and monitoring of pavement conditions by implementing participatory frameworks through smartphone apps that measure acceleration variations. The ensuing databases were used to train and test several machine learning algorithms. For the development of Asfalt [20], which classifies pavements as one of five categories (good, average, fair, poor and obstacle), the SVM with a polynomial kernel model outperformed other models, such as random forest, decision trees, k-nearest neighbors and naïve Bayes in what concerned both accuracy and computational effort. As for Streetcheck [23], this system instead aimed at a binary classification which differentiates stretches of a road as good or bad, for which random forests output the highest accuracy among several tested supervised learning algorithms (i.e., random forests, SVM, k-nearest neighbors (KNN) and J48).

Besides acceleration, image-based systems have also been used to determine pavement condition indexes. Majidifard et al. [68], for the surface distress detection approach, made use of image-based techniques and a deep machine learning hybrid model to predict a pavement surface condition index. This hybrid model consisted of the integration of the YOLO model to classify distresses and the U-NET model to quantify the severity of each class of distress. The distresses detected by the semantic segmentation model ranged from different types of cracks, such as transverse and longitudinal cracks, sealed cracks, alligator, and block cracks, to potholes. Concerning the prediction of the pavement condition index (PASER—pavement surface evaluation and rating), the authors applied three data-driven prediction models, namely gene expression programming (GEP), linear regression and weighted-based prediction in view of determining the best explanatory variables.

5.3. Structural Evaluation

5.3.1. Detection and Evaluation of Fatigue Cracking Progression

Since fatigue cracking is a result of cracks that develop inside the asphalt layers usually with a bottom-up direction, this kind of structural distress can be detected by monitoring the variation of pavement responses and comparing it with a reference response of an uncracked pavement. These fatigue cracking detection systems are either based on the variations of horizontal strain or vertical displacement [43,46,48,50], or acoustic wave propagation [42,53].

Some methods can detect cracks by monitoring the variations of acoustic signature of the pavement [42], which depend on the elastic modulus of the material. Fedele et al. [42] based his work on the hypothesis that the presence of cracks leads to a decrease in pavement characteristics, such as stiffness, and therefore a reduction in acoustic wave transmission. By evaluating the linear correlation of the elastic modulus (E) with the power spectral density (PSD) obtained from the acoustic signature, Fedele et al. proved the hypothesis that cracks can be detected by monitoring the acoustic signature. Ji et al. [53] also resorted to an acoustic-based method to estimate the width of cracks by applying linear regression analysis to a coefficient of acoustic wave attenuation.

Wang et al. [50] investigated the possibility of detecting cracks by resorting to optical fiber and FBG sensing techniques. While optical fiber was more adequate for distributed monitoring by being employed to measure the global mechanical properties, FBG was used for local detection of cracks and deformation with higher precision. Based on Bragg grating laws and Brillouin optical time domain analysis (BOTDA), the strain was measured in each sensing node. The detection of cracks was made possible by comparing two strain profiles: a reference one without cracks and one after cracking occurs.

Lenglet et al. [48] sought to anticipate damage by monitoring the strain profiles of pavement under realistic conditions and traffic. The method of detecting cracks followed the process of obtaining a reference strain profile of a pavement in good condition to compare with the strain profile measured. In this case, the reference profile was obtained by applying the linear elastic model of Burmister.

Instead of a deterministic approach, Alavi et al. [46] proposed a damage detection system which applies a stochastic approach to the detection of cracks based on the relationship between the probability density function (PDF) parameters obtained from strain distribution and damage progression of a bottom-up crack. In the same line, Hasni et al. [43] resorted to a probabilistic neural network (PNN), which classified the damage state of the pavement into four classes.

5.3.2. Estimation of Pavement Characteristics and Prediction of Mechanical Response

The accurate estimation of the pavement stiffness is crucial when it comes to the structural evaluation of a pavement. Currently, agencies leverage on FWD to evaluate the structural response of a pavement. By considering the theory of elasticity, it is possible to estimate the elastic modulus of the pavement layers through back-analysis. Thus, the main focus of the works described in this section was both the prediction of the mechanical response of the pavement under traffic load [49,51,52,54] or temperature effect [56], and the estimation of pavement characteristics, such as the elastic modulus of pavement layers. The latter was usually obtained through back-analysis supported by a structural model of the pavement, either by considering an elastic [49,51,52] or a viscoelastic [52,54] behavior.

Duong et al. [52] monitored an instrumented asphalt pavement section of a motorway and used that data to evaluate the mechanical properties of the different pavement layers. The elastic modulus was obtained by applying back-calculating techniques to the pavement mechanical model. The authors not only concluded that it is possible to continuously monitor a pavement section under real traffic, but they also evidenced the importance of analyzing the behavior of pavement layers and interfaces.

Ma et al. [54] developed a system to monitor airport asphalt pavement health that consisted of the instrumentation of a taxiway pavement with strain and stress sensors. The measured mechanical responses were used to update a mechanical model of the pavement. The latter was based on a multi-layered system theory, which adopts a viscoelastic behavior as a starting point to simulate the mechanical response of the asphalt pavement. The measured mechanical responses provided the basis both for the back-calculation of the elastic modulus of the pavement layers, by comparing them with the theoretical mechanical responses, and for the successive update of the mechanical model. Thereupon, the pavement damage from fatigue cracking and rutting was determined by applying transfer functions, which related the mechanical responses with the elastic modulus and the pavement performance. Additionally, the authors also explored a non-deterministic process for pavement distress prediction, which resorted to a neural network.

Zhao et al. [55] implemented a data-driven approach to assess the support conditions of rigid pavements. This was achieved by applying a probabilistic neural network to the extracted features associated with vibration signal detected by the optical fiber sensing arrays. Instead of using back-calculating techniques, some works investigated the possibility of estimating the elastic modulus by finding correlations between other characteristics of the pavement and the pavement modulus. Here, Cafiso et al. [45] demonstrated that extracted features from the vibro-acoustic signature of the pavement can have a good correlation with the pavement's elastic modulus.

6. Conclusions and Future Trends

This paper comprises a survey of the recent smart developments in the field of infrastructure monitoring contributing toward smart pavement environments. To achieve this, the work begins by firstly identifying the existent data collection methods in the context of pavement management and maintenance (Section 4), followed by a study on the relevant

analysis methods for the collected data, which, in turn, often result in decision support systems (Section 5).

The application of smart technologies, such as IoT and AI, to the field of pavement monitoring and condition evaluation will undoubtedly contribute to more efficient, less costly, safer, and environmentally friendly methodologies. All things considered, the main drive of the present work was to provide insight for the development of future decision support systems for smart pavement management by conducting a systematic literature review of the developed works that apply smart technologies to this field. In fact, future PMSs should tend to be capable of collecting and analyzing data at different levels, both externally at the surface or inside the pavement, as well as detecting and predicting all types of functional and structural flaws and defects.

Four key research questions (RQ) were identified and have supported the paper content. The first research question (RQ1) focuses on identifying the smart technologies that have been used or show significant potential of being applied to pavement condition monitoring. Throughout the literature review on this subject, these smart data collection methods were divided into external and embedded methods. While external methods were either smartphone-based sensors, or sensors installed in smart probe vehicles or drones, embedded methods could be either located inside the pavement or in fewer cases installed on the surface of the pavement. Some conclusions can be drawn from the content analysis of the selected reviewed papers belonging to each category of data collection method considered. Hence, in what concerns external data collection methods, which either focus on detecting surface distresses or pavement quality indexes, we conclude the following:

- The most used methods focus either on obtaining acceleration or image data. However, accelerometer-based solutions are less expensive while maintaining a reasonable efficiency compared with image-based methods. Indeed, despite featuring a higher reported effectiveness, the cost of these methods is higher, including in terms of computational requirements.
- An increasing interest in smartphones can be verified, especially when taking into account the opportunities that arise with interconnected devices as a complement to the traditional monitoring processes in view of minimizing the use of more expensive and precise equipment.
- Most recently, the interest in UAV-based methods has grown significantly as well, though the implementation of such methods by the industry still must overcome a significant number of obstacles related with flight permissions and low autonomy.

When it comes to embedded methods, which focus on the structural analysis of the pavement, we conclude the following:

- The emergence of these methods benefited from the extensive research in the field of concrete structure monitoring, and it was consequently initially applied to rigid pavements. Nonetheless, in the most recent years, the implementation of embedded sensorization is being broadened to include flexible pavements as well.
- Among embedded methods, piezoelectric sensors have been the subject of increased attention as a result of the advantages associated with not requiring an energy source, as they are able to produce their own while measuring strains and stresses in a sustainable way.

The second research question (RQ2) addresses the identification of data analysis methods based on smart technologies, such as artificial intelligence techniques. These methods were further divided according to the focus of the evaluation, which can either be functional or structural. On the one hand, functional evaluation can be either achieved by the detection of surface distresses or by the estimation of the pavement surface condition indexes. On the other hand, structural evaluation can focus on the detection of fatigue cracking, or on the estimation of pavement-intrinsic characteristics related with the structural capacity, such as the elastic modulus and the consequent prediction of the mechanical response.

From the analysis of the identified methods present in the literature, some conclusions can be drawn, firstly related with functional data analysis methods:

- These methods are mainly based either on acceleration data or on image-based data.
- The development of data-driven models applied to image-based datasets to detect surface distresses has been a subject of study for a long time, and many CNN architectures have been compared when applied to this problem. Currently, the tendency in image processing crack detection systems aided by data-driven models is to decrease computational effort by optimizing the hyperparameters of the ML model.
- Besides the significant implementation time and computational effort of data-driven models, such as CNN, other limitations can be pointed out, namely those related with the used database, which can compromise the efficiency and capacity of the model trained to make predictions on different databases.
- The estimation of pavement quality indexes is largely based on acceleration data, while the main difference between systems is related to either the machine learning model or the signal processing technique applied to the measured data.

Secondly, in relation to the works concerning the structural data analysis, we conclude the following:

- Most methods are based on the estimation of the pavement elastic modulus, with the objective of either detecting fatigue cracking or predicting the mechanical response. The elastic modulus is typically obtained by back-analysis supported by mechanical models, or more recently by finding correlations with other pavement characteristics such as the pavement vibro-acoustic signature.
- Fatigue cracking is detected by comparing the current behavior of the pavement with a reference behavior of a healthy pavement. This reference could be based on the strain and stress signal or on the acoustic signal of the pavement.
- When it comes to the prediction of the pavement mechanical response, the current tendency seems to be the improvement of the mechanical models that simulate the mechanical response, which are also used to estimate the elastic modulus by back-calculation. Traditional FWD-based methodologies adopt the elastic theory to assess the structural response of the pavement. Yet, as it was proven by several recent studies, the resulting models are not able to capture the behavior of a flexible pavement effectively since its behavior is more akin to a viscoelastic material.

Many of the developed systems presented in the literature have already integrated the whole process of a pavement management system from data collection, data analysis and decision support visualization tools (RQ3) in an automated, seamless system for surface condition monitoring [19,20,22,23,25,27]. Smartphone-based systems are an example of an easily implementable tool that can encompass all of these three modules of a PMS. However, presently, these systems are exclusively used to evaluate the surface condition, i.e., a functional level evaluation.

When considering a pavement monitoring system which integrates both smart data collection and data analysis methods and features the capability to assess pavement both functionally and structurally (RQ4), the literature reveals a lack of such ubiquitous systems. Notwithstanding the fact that the pavement monitoring systems developed today already integrate smart data collection and data analysis methods, these still focus on either a functional or structural evaluation. Thus, noteworthy directions for future work in this field may include the exploration and/or improvement of the following topics:

- Optimization of sensor placement for smartphone-based systems. The smartphone placement inside the vehicle can be further optimized and standardized or be taken into account in the analysis as a feature.
- Route planning and optimization in case of dynamic monitoring, such as smart probe vehicles and UAV. Bearing in mind that UAV usually have a low autonomy, the routes have a greater need of being optimized to cover more sections of the network in a single run.

- Since the exploration of embedded solutions is somewhat recent, there is still a research gap regarding the effects of using such methods in the long run. Future research of embedded sensors may also focus on studying the impact of the presence of sensors inside the pavement, regarding both the pavement performance and life cycle assessment, along with the evaluation of sensor survivability for long-term applications.
- Crowdsourcing smartphone-based systems and connected vehicles can be leveraged to collect large volumes of data that can significantly improve the accuracy of infrastructure agencies' own collected data.
- Consequently, those systems enable the creation of unified databases to generalize the application of trained ML models, aiming at eliminating the decrease in efficiency when these models are applied to different databases. This aspect can be extended to include standardized public ML training databases from which models can be trained up to a certain performance level by any researcher. This would ultimately allow for further studies to be carried out from that point onward, similar to the databases used to train convolutional neural networks in the image classification field, such as the well-known VGG-16 [69] or the ResNet50 [70] databases.
- The integration of both smart external and embedded data collection methods covers functional and structural evaluation simultaneously and in a continuous, dynamic way. This would not only allow for the monitorization of a greater area of the network for less time and resources, but also benefit the performance of decision support systems. Ultimately, this would result in a comprehensive smart pavement management system that could aid the infrastructure agencies by supporting decision making from a holistic perspective.

Author Contributions: Conceptualization, M.P., J.N. and P.F.; Methodology, M.P., J.N. and P.F.; Validation, M.A., M.P. and J.N.; Formal analysis, M.A.; Investigation, M.A.; Writing—original draft, M.A. and M.P.; Writing—review & editing, M.A., M.P., J.N. and P.F.; Visualization, M.P. and P.F. All authors have read and agreed to the published version of the manuscript.

Funding: This work is supported by European Structural and Investment Funds in the FEDER component, through the Operational Competitiveness and Internationalization Programme (COMPETE 2020) and Lisbon Regional Operational Programme (ROP Lisbon) [Project n.º 046123; Funding Reference: POCI-01-0247-FEDER-046123 and LISBOA-01-0247-FEDER-046123]. It is also supported by the Highly Qualified Human Resources programme [Funding Reference: NORTE-06-3559-FSE-000116].

Data Availability Statement: Not applicable.

Acknowledgments: The authors gratefully acknowledge the support of CERIS (Civil Engineering Research and Innovation for Sustainability). Furthermore, the authors would like to express their gratitude to all members of the Portuguese Committee of Geotechnics for Transportation (CPGT) of the Portuguese Geotechnical Society (SPG) for relevant formal and informal discussions, comments and remarks which aided the development of this work.

Conflicts of Interest: The authors declare no conflict of interest.

Abbreviations

The following abbreviations were used in this manuscript:

AI	Artificial intelligence
BOTDA	Brillouin optical time domain analysis
CNN	Convolutional neural networks
DSS	Decision support systems
DTPS	Dynamic tire pressure sensor
E	Elastic modulus
FBG	Fiber Bragg grating sensors
FWD	Falling weight deflectometer
GEP	Gene expression programming
GPR	Ground-penetrating radar

GPS	Global positioning system
IoT	Internet of things
IRI	International roughness index
KNN	K-nearest neighbors
LiDAR	Light detection and ranging
ML	Machine learning
M&R	Maintenance and rehabilitation
PASER	Pavement surface evaluation and rating
PCI	Pavement condition index
PDF	Probability density function
PMS	Pavement management systems
PNN	Probabilistic neural network
PPI	Pavement performance index
PSD	Power spectral density
PSI	Present serviceability index
RMS	Root mean squared
RQ	Research question
SfM	Structure from motion
SPA	Self-powered damage-detection aggregate
SVM	Support vector machines
UAV	Unmanned aerial vehicle
YOLO	You only look once

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