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Review

A survey on CSI-based Wi-Fi sensing datasets and models with a focus on reproducibility

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ABSTRACT

Wi-Fi sensing based on Channel State Information (CSI) has witnessed considerable research activity in recent years. However, a critical literature analysis reveals that only a limited amount of proposals are potentially reproducible, with many works lacking essential experimental details, publicly available datasets, or accessible analysis code. This may impede the research progress and the subsequent transition of promising findings into practical applications. The objective of this work is to identify CSI-based sensing proposals that are potentially reproducible based on the published information. Our goal is to provide a focused review of resources that can serve as a concrete starting point for researchers and practitioners seeking to experiment with and advance the field of Wi-Fi sensing. We perform a comprehensive analysis of publicly available datasets (encompassing both the collection methodologies and the environmental characteristics) and existing sensing models, accompanied by their code, pre-processing steps, and evaluation procedures. Finally, we discuss what are the minimum requirements for truly verifiable contributions in this field, and outline the best practices for creating and sharing reproducible CSI-based sensing datasets and models.

Contents

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1. Introduction

Research on Channel State Information (CSI) based sensing with Wi-Fi has been very active and prolific in the past years. Ever since the first evidence that Artificial Intelligence (AI) and Machine Learning (ML) algorithms could extract meaningful information from the CSI analysis at the beginning of the past decade [1,2], a flourish of proposals, methods, and experiments appeared in the literature, spawning further research and rising also the attention of industries and standardization bodies [3].

A thorough review of the literature, however, reveals that only a fraction of the papers appear to be *reproducible*. Many works are based on experiments where details are missing, the dataset is not released publicly, or the code used to analyze the CSI is not available . . . or all of this is missing. This is hampering research and, as a consequence, the transition from labs to startups and finally to the market. This observation is the main drive that motivated this work: What are the proposals falling under the umbrella of CSI-*based sensing* that may be reproduced based on the published information? We define a work as reproducible if at least two of the following four conditions are met: *(i)* The tool used to extract the CSI from the Wi-Fi chipset is declared; *(ii)* The data of the experiments is published as Open Data, so that results can be validated or falsified; *(iii)* The classification or inference algorithm used is described with sufficient detail to enable the reader to set out to code it; or *(iv)* The code of the algorithm above is Open Source. Clearly, for a work to be truly Open Science, all four conditions should be met. However, our analysis shows that very few works meet this standard; thus, we relaxed this requirement.

The goal of this work, is to collect in a single review the proposals and tools that can be the starting point for someone (researcher, network manager, service designer, etc.) who wants to experiment with CSI sensing and push the state of the art one step beyond.

The reproducibility of experiments is a foundation of science. It is so important that UNESCO provides a set of guiding principles for the *open scientific knowledge* [4], emphasizing the importance of transparency, accessibility, and sharing of scientific results. These principles are summarized in Fig. 1 and include scientific publications, research data (e.g., raw or processed data, metadata), and software source code, which are the subject of this survey and highlighted in green. Educational resources and hardware are instead outside the scope of this work and circled in yellow.

In this survey, we analyze scientific papers dealing with CSI-Sensing (CSIS) to analyze if and how they adhere to principles of open scientific knowledge. ML or Deep Learning (DL) methods for CSIS, in fact, are data-driven and therefore strongly depend on the training and evaluation data, the implementation details, and the experimental setup. We focus on two specific aspects that we believe are essential to the reproducibility of scientific research: *(i)* the use of publicly available datasets for experimental evaluation (**Open Data**), and *(ii)* the public availability of the source code used for the experimental campaign (**Open Source Code**).

First, we look at the datasets; as with other tasks, such as image classification, establishing benchmarks helps develop new models and compare the performance of different proposals on a common ground. For each dataset, we consider the hardware and software configurations used to collect the data, the information on the accuracy of the ground-truth identification and other physical characteristics of the environment, as well as the sensing tasks the dataset focuses on. Then we analyze the reproducibility of the model. For each paper, we consider which dataset they use, whether the preprocessing steps are clearly described or the code for such preprocessing is released, and the availability of the code that implements the proposed model (along with all the configuration requirements), the scripts for setting up the tool and running the tests, and a description of how to use the tool.

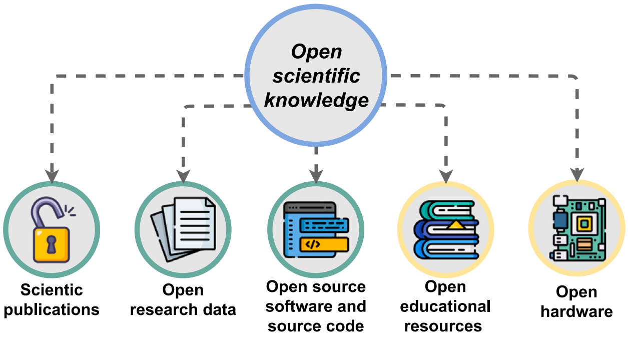

Fig. 1. The main principles of *Open scientific knowledge*. The principles considered in this work are the ones highlighted in red, and refer to the possibility of reproducing, and hence validate or falsify, results reported in scientific literature, highlighted in red. Education and hardware are outside the scope of this work.

This analysis allows the identification of a set of minimum requirements that both the dataset and the model should have to be considered as a reference for any future work. In summary, we make the following contributions:

- We provide an overview of the publicly available datasets, with information about the tools used, the characteristics of the test environments, and the sensing tasks;
- We review the various proposals for CSI sensing, focusing on the code required to set up the computational environment, the model itself, and the evaluation;
- We discuss the requirements and best practices for creating a dataset and a model, and making them available. We also discuss the challenges and future directions for CSI sensing.

2. Background and related work

Wireless sensing research distinguishes two main paradigms: **device-based** (or *active*) and **device-free** (or *passive*) approaches. Device-based methods explicitly require active cooperation of a device (e.g., smartphones, smartwatches, RFID tags), and hence relate to the device itself and only indirectly to the person who carries it. Device-free approaches, instead, rely on signal perturbations caused by changes in the environment, and in particular by human presence or movements. Specifically, these methods leverage ubiquitous Radio Frequency (RF) systems—e.g., Wi-Fi, Radio Frequency Identification (RFID), or cellular—to correlate specific measures and metrics to the changes in the propagation characteristics of RF signals, including variations in amplitude, phase, and multipath effects. Recent surveys [5,6] have highlighted the benefits of device-free sensing methods over device-based ones, emphasizing their flexibility and non-intrusiveness, particularly in indoor environments where deploying wearable devices can be impractical or inconvenient due to user non-compliance, comfort constraints, limited battery life of wearable devices, and deployment complexity.

Many related studies have reviewed device-free methods, highlighting their applications, challenges, and advancements [7–10]. These methods can be divided into **radar-based** and **Wi-Fi-based** approaches (the latter also applicable to cellular systems) since they are based on the same idea of exploiting the channel state information, or channel sounding, already used to equalize and optimize data transmission. Radar systems actively transmit RF signals and analyze reflections to recognize motion and activity with high accuracy, making them ideal for applications requiring fine-grained recognition capabilities. Among this category, Software Defined Radio (SDR)-based radar systems stand out for their flexibility in reconfiguring signal parameters in real-time via software, allowing adaptation to different sensing scenarios. However, despite their effectiveness, large-scale deployment of SDR-based systems remains challenging due to the high cost of specialized hardware and the complexity of installation [11]. Radar systems, though very interesting, are outside the scope of this work.

In contrast, Wi-Fi-based sensing leverages existing Commercial Off-The-Shelf (COTS) Wi-Fi infrastructure, making it a cost-effective and easily deployable alternative. These methods analyze the characteristics of the propagation environment induced by human presence, movement, or other changes using either the simple Received Signal Strength Indicator (RSSI) and/or the more sophisticated CSI. Many surveys [5–8,11,12] have extensively investigated the advancements of RSSI and CSI-based approaches, highlighting the superiority of CSI in terms of accuracy, robustness, and applicability for fine-grained human activity recognition [13–15]. RSSI is a single value per packet representing the energy of the frame received, while CSI-based sensing considers amplitude and phase variations across multiple subcarriers [7,13] of Orthogonal Frequency Division Multiplexing (OFDM) symbols, enabling more precise and detailed sensing capabilities.

Numerous studies have focused exclusively on CSI-based approaches, exploring their potential and conducting extensive evaluations from various perspectives [5,7–12,16–25]. While most surveys broadly analyzed their strengths, limitations, and advancements, some works adopted a more specific perspective. For instance, [24] investigated the feasibility of deploying CSI-based sensing on resource-constrained edge devices, evaluating practical key aspects such as sampling rates, computational overhead, inference rates, and energy consumption to enable real-time sensing on low-cost hardware. Similarly, [19] focused on sensing in through-the-wall scenarios, exploring how wireless signals can penetrate walls to enable recognition across different rooms. Hence, it discussed typical challenges related to signal attenuation and environmental change and compared through-the-wall with non-through-the-wall approaches. In contrast, [23] examined the robustness of these approaches in cross-domain scenarios. The study analyzes how different factors—such as noise, environmental conditions, user characteristics, and device configurations—affect CSI parameters. Additionally, it investigates commonly used preprocessing techniques, highlights their limitations, and explores advanced strategies to overcome these challenges.

Some surveys on CSI-based approaches classify works on **model-based** and **learning-based** (also known as *pattern-based*) methods [5–7,15,17,18,23,26,27]. Model-based approaches address sensing applications by leveraging mathematical or physical models to describe the relationship between CSI variations and human behavior. They rely on principles such as Time-of-Flight (ToF), Angle-of-Arrival (AoA), and Fresnel zone models [18]. While these methods require fewer data samples since they do not rely on extensive training, they struggle to generalize in complex environments where modeling all propagation effects is particularly challenging. Learning-based approaches aim to identify unique patterns in CSI variations by leveraging data-driven techniques based on ML and DL. Given the strong dependency of such approaches on data, the effort required to collect large amounts of high-quality, variegated, and reliably labeled training data is a key challenge [28]. Some studies highlight the lack of standardized datasets, which hinders the reproducibility and the development of generalizable solutions [18,29]. Other limitations include the susceptibility to overfitting, the struggle to adapt to domain changes, and the significant computational resources for training and deployment [9,20].

Overall, the focus of our analysis on learning-based approaches is motivated by the growing body of research in this area. ML and DL techniques can autonomously extract features to handle complex, high-dimensional data. They have been widely adopted to address sensing applications (viz. tasks) at different levels of granularity [17,18], from tracking subtle movements, such as heartbeat and respiration [22], to hand/sign gesture recognition and body gesture recognition, to fall detection, intrusion detection, and user identification tasks.

Positioning and Survey Scope Existing surveys on CSI-based sensing mainly focus on technological advancements, methodologies, and applications, providing a solid theoretical and methodological basis. However, they mostly overlook *reproducibility*, and do not adequately address the practical difficulties researchers face, especially those new to the field. Specifically, early-stage researchers often struggle to find accessible, well-documented resources to start their work. Although publicly available datasets, CSI collection tools, and preprocessing and analysis methods exist, we noticed that often they are fragmented, incomplete, or poorly documented, making them difficult to use effectively.

Only a few works focused on the employed CSI extraction tools [5,6,10,22,25] and datasets [9,10,25,28], but they remain descriptive rather than critical, providing a limited dataset overview and lacking detailed comparisons of the strengths and limitations of existing tools. Instead, we systematically review potentially reproducible CSI-based sensing studies to bridge this gap, offering practical insights rather than just a theoretical overview. More in detail:

- We provide a detailed analysis of currently available CSI collection tools, examining their functionalities and limitations;
- We deliver a comprehensive overview of publicly available datasets, examining them from different perspectives, including collection instrumentation, user characteristics, collection environments, and enabled sensing applications;
- We analyze open-source code in detail, assessing its potential usability for replicating previous research. Given its critical role in reproducibility, we examine key aspects such as dependencies, training and evaluation scripts, and overall documentation quality to determine how effectively researchers can build upon existing work;
- We provide direct links for easy access to CSI tools, datasets, and code repositories, enhancing transparency and ensuring ease of use for researchers.

With this work, we intend to create a practical starting point for researchers, engineers, and practitioners interested in experimenting with CSI-based sensing, ensuring they can access the necessary tools and resources for rigorous and reproducible research. There are several works [14,30–57], most of which have been described in existing surveys, for which, we have not been able to find sufficient information about the CSI extraction tools, the dataset is not publicly available, and the code is not open or well described—three of the four conditions for potential reproducibility mentioned in the Introduction. Therefore, we will not discuss these papers, even though they have been reviewed and cited extensively in the past.

In summary, our work complements previous research by bridging the gap between speculative findings and actual contributions and knowledge with real-world implementation, ultimately facilitating future research and development in this area.

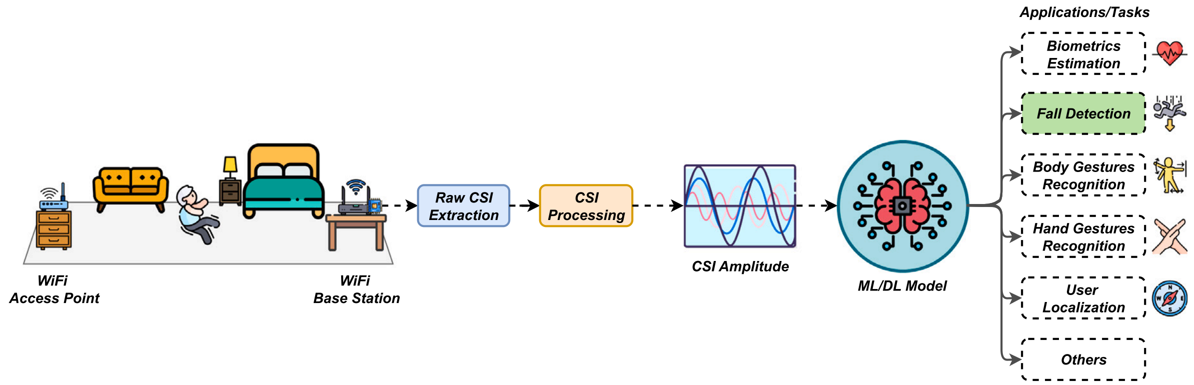

Fig. 2. Overview of the CSI processing chain for Wi-Fi perceptive networks. A Wi-Fi device collects data from ongoing transmissions to enable advanced sensing applications. Specific devices can work with different bandwidths or Wi-Fi versions and can collect the CSI of up to $N_t \times N_r$ distinct links from each Wi-Fi frame. The type of processing strictly depends on the target application.

2.1. Channel state information

In wireless communication systems, the CSI describes how a signal propagates from the transmitter to the receiver through the wireless channel. By capturing the effects caused by reflection, scattering, diffraction, and multipath propagation on the wireless signals, the CSI is essential to optimize communication performance and enable advanced functionalities such as beamforming, adaptive modulation, and resource allocation. In an OFDM system like Wi-Fi, the CSI offers a fine-grained estimation of the wireless channel's behavior in the frequency domain. For this reason, thanks to the large bandwidth of the Wi-Fi signals and the granularity of OFDM subcarriers, this information is particularly valuable not only for optimizing communication functions but also for device-free sensing applications such as gesture recognition, indoor localization, and human activity monitoring.

Mathematically, given an OFDM system with N subcarriers and a single spatial stream, the wireless channel between the transmitter and the receiver can be modeled in the frequency domain using the following equation:

$$\mathbf{y} = \mathbf{h} \otimes \mathbf{x} + \mathbf{n} \tag{1}$$

where $\mathbf{y} \in \mathbb{C}^{\mathrm{N}}$ is the received OFDM symbol, $\mathbf{h} \in \mathbb{C}^{\mathrm{N}}$ is the frequency response of the wireless channel, $\mathbf{x} \in \mathbb{C}^{\mathrm{N}}$ is the transmitted OFDM symbol, and $\mathbf{n} \in \mathbb{C}^{\mathrm{N}}$ is the noise vector. The symbol $\otimes$ indicates the Hadamard product—i.e., the element-wise multiplication of two vectors. In Eq. (1), the channel $\mathbf{h}$ defines the amplitude and phase shifts experienced by each transmitted subcarrier. With this model, the receiver estimates the channel response $\mathbf{h}$ by calculating the CSI $\mathbf{C} \simeq \mathbf{h}$ over a known field in the Wi-Fi preamble—i.e., by computing the ratio between the received signal $\mathbf{y}$ and the transmitted signal $\mathbf{x}$.

In CSI-based Wi-Fi sensing applications, amplitude and phase variations within the CSI are important because they encode the reflections, scattering, and Doppler effects induced by human presence (or movements) and other environmental changes. In general, a larger bandwidth and reduced spacing between OFDM subcarriers allow for higher frequency resolution and more detailed observation of multipath components in the wireless channel. This improves sensitivity to small movements and increases the separability of different propagation paths, thereby enhancing the accuracy and robustness of sensing tasks. Indeed, as a direct consequence of frequency analysis, larger CSI bandwidth yields higher resolution in the time domain, allowing for a more accurate discrimination of multipath components; on the other hand, higher frequency resolution in the CSI—i.e., reduced OFDM spacing—yields the capability of detecting multipath components with larger delays. Moreover, in Multiple-Input Multiple-Output (MIMO) systems, with $\mathrm{N_t}$ transmit and $\mathrm{N_r}$ receive antennas, the CSI becomes a tensor with $\mathrm{N_t} \times \mathrm{N_r} \times \mathrm{N}$ elements since $\mathrm{N_t} \times \mathrm{N_r}$ orthogonal spatial streams are established between the nodes. Since Eq. (1) holds for each separate spatial stream, it is apparent that MIMO configurations can significantly increase the sensing capabilities of the sensing systems by augmenting the amount of information in the CSI.

Fig. 2 illustrates the typical data collection process and applications of Wi-Fi sensing. First, a device listens to communications over the air on the shared medium, measuring the CSI for each received Wi-Fi packet. The CSI is affected not only by the layout of the room and the presence of furniture, but also by the location and movements of people, which modify the properties of the channels and the electromagnetic propagation of each Wi-Fi frame. Although this information is crucial for signal equalization, beamforming, or MIMO precoding, general-purpose processors can also elaborate and analyze collected CSI data to enable various sensing applications, ranging from gesture/activity recognition to device-free localization and beyond. However, despite that all Wi-Fi devices are required to compute the CSI for communication-related tasks, this information does not typically leave the transceiver chipset and is kept away from the user. For this reason, several tools have been proposed in the last decade to access this information, which can then be stored and further analyzed. Such tools take the name of CSI extractors, and the most popular are described in the next part of this section.

2.2. CSI extraction tools

CSI extractors are essential to perform any sensing based on CSI analysis. They are basically a probe capable of extracting CSI data from the Wi-Fi chipset and presenting it through a proper Application Programming Interface (API) for further analysis. As the standardization of Integrated Sensing and Communications (ISAC) progresses, it is desirable that Wi-Fi chipsets manufacturers will converge to a common API that directly exposes the CSI. So far, however, since CSI extractors need to interact with commercial radio hardware at a very low level, the research community has proposed several different tools, each compatible with different Wi-Fi chipsets and standards. Today, there is no general CSI extraction tool working on all Wi-Fi devices, and the quality and format of the output data also vary significantly.

Table 1 reports the most popular tools used in the scientific literature, summarizing the main features and highlighting their differences. As we discuss in Section 3, the properties of the data collected by each extractor are strongly tied to the quality and the type of processing needed for different sensing applications.

To our knowledge, the first tool publicly available for the research community was the Linux 802.11n CSI extractor [58], which was released in 2011. It is based on the Intel WL 5300 Wi-Fi chipset, and it is still the most common CSI extraction tool in many research works. It supports single-stream transmissions with a maximum bandwidth of

Table 1
CSI extraction tools.

Tool name	Year	Wi-Fi	Max BW	MIMO	Subcarriers	Supported Wi-Fi Chipsets	Free license	Open source	Access
Linux 802.11n CSI [58]	2011	4 (n)	40 MHz	–	30	Intel WL 5300	✅	✅	⬇
OpenRF [59]	2013	4 (n)	40 MHz	–	30	Intel WL 5300	✅	—	🚫
Atheros CSI [60]	2015	4 (n)	40 MHz	–	56 – 112	Atheros AR9580, AR9590AR9344, QCA9558	✅	✅	⬇
Nexmon CSI [61]	2018	5 (ac)	80 MHz	4 × 4	up to 256 × 16	Broadcom 4339, 43458 43455c0, 4366c0	✅	✅	⬇
ESP32 [24]	2020	4 (n)	20 MHz	–	64	ESP32-WROOM-32	✅	✅	⬇
PicoScenes [62]	2022	6 (ax)	160 MHz	2 × 2	up to 1992 × 4	Intel AX200/210, WL 5300 Atheros QCA9300	☑	⊗	◉
AX-CSI [63]	2022	6 (ax)	160 MHz	4 × 4	up to 2048 × 16	Broadcom 43684	✅	⊗	✉
FeitCSI [64]	2024	6 (ax)	160 MHz	2 × 2	up to 2048 × 4	Intel AX200/210	✅	✅	◉

License: Free (✅), Limited Free/Paid Features (☑). *Open Source*: Yes (✅), No (⊗), No Longer Available (—).
Access: Direct download (⬇), Download no longer available (🚫), Ubuntu Package (◉), On Demand (✉).

40 MHz and can only report the value of 30 OFDM subcarriers (roughly one subcarrier every two in 20-MHz transmissions or one every four in 40-MHz transmissions).

The tool was further extended in [59] to support channel reconfiguration and beamforming capabilities. Other tools with similar features but designed to be used with other chipset manufacturers are the Atheros CSI software [60] and the ESP32 extractor [24].

Nexmon CSI [61] enables CSI extraction from a wide range of Broadcom 802.11ac chipsets. It supports up to 4 × 4 MIMO with 80 MHz bandwidth, greatly expanding the number of data points collected for each incoming Wi-Fi packet compared to other CSI extractors.

Finally, the last three entries in Table 1 report the most recent tools that support CSI extraction also from 802.11ax frames. PicoScenes [62] works with several Intel and QCA Wi-Fi chipsets, with up to 2 × 2 MIMO configurations. The recent Intel AX200/210 chipsets are also supported with the same functionalities by FeitCSI [64], which—in contrast to Picoscenes—is free and open-source. AX-CSI [63] only works on specific Broadcom chipsets but can work with up to 4 × 4 MIMO frames. All these three CSI extractors support the most peculiar features of 802.11ax; namely, the larger channel bandwidth of 160 MHz and more OFDM subcarriers (because the subcarrier spacing was reduced by a factor of 4 from 802.11ac to ax).

3. Publicly available CSI datasets

This section delves into the publicly available datasets for CSIS. Data plays a crucial role in developing ML-based models to address CSIS tasks, as the quality and diversity of data directly affect their performance and generalizability.

The main challenge is related to the continuously changing channel state. The changes may be related to the environment, such as the furniture moved in the room, and to user behavior. Thus, gathering data reflecting diverse environmental and user scenarios is a fundamental step toward building robust models that adapt to different or even *unseen* scenarios.

Table 2 summarizes the available public datasets that we were able to identify at the time of writing. For each dataset, we analyze the following key aspects: the hardware and software configurations used for data collection (ref. Section 3.1), the characteristics of the users involved (ref. Section 3.2) and the collection environments (ref. Section 3.3), and the ground truth information provided (ref. Section 3.4)—i.e., the sensing tasks they enable. Lastly, we discuss the release mode and format of each dataset (ref. Section 3.5).

3.1. Hardware and software setup

Most of the reviewed datasets in Table 2 were collected using the Linux 802.11n CSI (L-CSI) tool (**Tool** column) installed on an Intel WL 5300 (i5300) network adapter (**NIC** column). Conversely, others were collected using Atheros CSI (A-CSI) [76,77,80], Nexmon CSI (N-CSI) [74,82,83,86,91], or ESP32 [81,90]. Only [84] was collected using the AX-CSI tool, which, unlike others, can take advantage of the potential offered by 802.11ax. Except for L-CSI, due to the greater number of Network Interface Cards (NICs) supported by the other tools, it was not possible to trace the NIC specifications used unless explicitly stated.

Because of the technological limitations of the adopted tools, all datasets leveraging L-CSI/OpenRF, A-CSI, or ESP32 were collected employing the now-old 802.11n Wi-Fi networks (**802.11** column). Conversely, those obtained using N-CSI [74,82–84,91,92] and AX-CSI [84] comply with the more recent 802.11ac and 802.11ax standards. In this regard, we notice that the collection procedures do not keep pace with the progress of wireless standards and extraction tools and that the scientific community mostly relies on legacy methods.

On the other hand, we observe that most data collection happens in the of 5GHz ISM (Industrial, Scientific, and Medical) band (**Freq.** column). Typically, this band is preferred over the 2.4GHz ISM band because there is less interference with other devices (e.g., smartphones, Wi-Fi routers, home automation wireless protocols, microwave ovens, etc.).

Due to the heterogeneous properties of the CSI extractors, each data collection setup can use a different MIMO configuration with a different number of transmitting and receiving antennas. The different pairs of transmitting-receiving antennas (*spatial streams*) represent the independent data streams that can be sent simultaneously by exploiting the different trajectories in the communication channel.

Most setups used an asymmetric configuration with 1 transmitting and up to 4 receiving antennas (**C** column). In other cases, a symmetrical setup with an equal number of antennas was used (i.e., 1 to 3) [67–69,71,74,76,78,82,84,89,91], while only one employed more transmitting antennas than receiving antennas (i.e., 3 vs. 1) [65].

Since most of the works are based on L-CSI, most of the collected datasets are based on narrow channels with a bandwidth of 20MHz (**Bw** column) and 30 sub-carriers per antenna per spatial stream (**N** column)—i.e., only 30 data points per CSI. However, wider channels and more subcarriers may improve sensing accuracy by offering higher

Table 2
Public CSI datasets.

Year	Name	HW & SW Setup										Users				Environments			CSI Task		Plat.
		NIC	Tool	802.11	Freq. [GHz]	Bw [MHz]	N	C[$\mathbf{T_x} \times \mathbf{R_x}$]	$\mathbf{S_r}$ [kHz]	Time Coverage	Data	👥	⚥	🎂	⚖	#	Type	🪑	GT	#	
2017	UT-HAR [8]	i5300	L-CSI	n	-	20	30	1 × 3	1.0	-	FULL	6	○	○	○	1	office	○	BG	6	△
2018	SignFi [65]	i5300	Openrf	n	5.0	20	30	3 × 1	0.2	Oct.-Nov., 2017 Jun.- Jul.,2017	FULL	5	○	●	●	2	lab, bedroom	●	SP	276	box
	FallDeFi [66]	i5300	L-CSI	n	5.0	20	30	3 × 3	1.0	-	FULL	3	○	●	●	5	corridor, bathroom, bedroom, kitchen, lab	●	FD BG	4	M
	Zhang18 [67]	i5300	L-CSI	n	5.0	20	30	3 × 3	1.0	–	–	100	●	○	●	3	hall, corridor, room	●	BG	40	✉
	Wang18 [68]	i5300	L-CSI	n	5.0	-	30	1 × 1	0.1	-	AMP	30	●	○	●	1	room	-	BE HID SP FD	- 30 10 2	🐙
2019	ARIL [69]	–	–	n	–	20	52	1 × 1	–	–	FULL	1	–	–	–	1†	room	○	HG × UL	6 × 16	△
	WiAR [70]	i5300	L-CSI	n	5.0	20	30	1 × 3	0.03	-	FULL	10	●	○	●	3	empty, office meeting room	●	BG	16	🐙
	SAR [71]	i5300	L-CSI	n	2.4	20	30	3 × 3	0.05	6d	FULL	9	○	○	○	1	studio	●	BG	6	4TU
2020	Alazrai20 [72]	i5300	L-CSI	n	2.4	20	30	2 × 3	-	-	FULL	66	●	●	●	1		●	HHI	12	⁂
	CSLOS [73]	i5300	L-CSI	n	2.4	20	30	1 × 3	0.32	–	FULL	30	●	●	●	3	lab, office, hall	●	BG	12	🐙
2021	CSI-HAR [74]	Broadcom	N-CSI	ac	5.0	20	52	1 × 1	0.2	-	AMP	3	○	●	○	1	bedroom	●	BG	7	△
	Xiao21 [75]	i5300	L-CSI	n	2.4	20	30	1 × 3	0.05	–	FULL	5	○	●	●	1	meeting room	●	HG BG	5 5	△
	Zhuravchak22 [76]	Atheros	A-CSI	n	5.0	40	114	2 × 2	-	-	FULL	1	-	-	-	3	room	-	BG	7	✺
2022	CSIDA [77]	Atheros	A-CSI	n	5.0	40	114	1 × 3	1.0	–	FULL	5	●	○	○	2	office, classroom	●	HG	6	🐾
	OPERAnet [78]	i5300	L-CSI	n	5.0	20	20	3 × 3	1.6	-	FULL	6	○	○	○	2	office	●	BG PC UL	6 6 -	✺
	Widar3.0 [79]	i5300	L-CSI	n	5.0	20	30	1 × 3	1.0	–	FULL, BVP	16	●	●	●	3	classroom, hall, office	●	HG HG	6 10	◈
	NTU-Fi-HAR [80]	Atheros	A-CSI‡	n	5.0	40	114	1 × 3	0.5	-	AMP	20	●	○	○	1	lab	●	BG	6	△
	NTU-Fi-HID [80]	Atheros	A-CSI‡	n	5.0	40	114	1 × 3	0.5	–	AMP	15	●	○	○	1	lab	●	HID	?	△
	Choi22 [81]	ESP32	ESP32	n	2.4	20	52	1	0.1	3d	$\overline{\text{AMP}}$	5,10	○	○	○	2	meeting room, seminar room	●	PC CL	10 4	🐙
	AntiSense [82]	Broadcom	N-CSI	ac	5.0	80	242	1 × 1	1	23d	FULL	1	–	–	–	1	lab	○	UL	8	Ze
2023	Meneghello23 [83]	Broadcom	N-CSI	ac	5.0	80	242	1 × 4	0.16	Apr.-Dec. 2020 Jan.2022	FULL	3	●	○	○	3	bedroom, lab, living room	●	BG	5	DATA
	Cominelli23 [84]	Broadcom	AX-CSI	ac, ax	5.0	20 – 160	64 – 2048	1 × 11 × 4	0.15	2d	FULL	3	○	○	○	3	lab, office, hall	●	BG	12	Ze
	⟊ FallDar [85]	-	-	n	5.0	20	30	1 × 3	1.0	11d	FULL	3 + 1	○	○	○	3	living, dining, balcony	●	FD	6	∞
2024	Bian24 [86]	Broadcom	N-CSI	ac	5.0	80	256	1 × 4	0.1	–	FULL	20	○	○	○	1	meeting room	●	HID	20	◈
	Wi-Mir [87]	i5300	L-CSI	n	5.0	20	30	3 × 3	0.95	-	FULL	6	○	●	●	1	lab	●	HHI	17	❖
	WiSense [88]	i5300	L-CSI	n	2.4	20	30	3 × 3	0.1	–	FULL	10	○	○	○	2	meeting room, office	●	BG	6	🐙
	WiMANS [89]	i5300	L-CSI	n	2.4 + 5.0	-	30	3 × 3	1.0	-	FULL	6	●	●	●	3	empty, meeting, classroom	●	HID/UL/BG	9	k
	CP-HAR [90]	ESP32	ESP32	n	2.4	20	32	1 × 1	0.063	–	FULL	5	○	○	●	1	room	○	BG	7	🐾
2025	Tonini25 [91]	Broadcom	N-CSI	ac, ax	5.0	20 40 80	256 512 1024	1 × 1	0.03	5d	FULL RAW	5	●	●	●	2	office, lab	●	PC	5	Ze

Bw: Bandwidth/Channel width, N: Numb. of subcarriers, C: Numb. of streams, $\mathbf{S_r}$: Sampling-rate,
FULL: Complete CSI (i.e., amplitude and phase), AMP: CSI Amplitude, $\overline{\text{AMP}}$: pre-processed CSI Amplitude, RAW: Raw PCAP traces, BVP: Body-coordinate velocity profile
i5300: Intel WL 5300, L-CSI: Linux 802.11n CSI, A-CSI: Atheros CSI, N-CSI: Nexmon CSI, ‡: Custom CSI Tool, 👥: Number of users, ⚥: Gender, 🎂: Age, ⚖: Physical Attributes, †: same room with different indoor locations.
4TU: 4TU.ResearchData, 🐾: Baidu, box: Box, △: Google Drive, ❖: Dropbox, ✺: Figshare, 🐙: GitHub, ◈: IEEE Dataport, k: Kaggle, M: Mega, ⁂: Mendeley, DATA: Research Data Unipd, ∞: Sensing Dataset Platform, Ze: Zenodo,
✉: Under Request. Plat.: Hosting Platform. ⟊: The description in the reference paper differs from the one on the release site, so we have chosen to refer to the latter.

frequency resolution and enhanced multipath differentiation. This enables a more detailed detection of environmental and user-induced changes in CSI [84].

Some works relied on a wider channel bandwidth, ranging from 40 MHz [76,77,80,91] to 80MHz [82,83,91], and at least ≈4× more subcarriers—i.e., between 114 and 1024. Cominelli et al. [84] leveraged the 802.11ax features to reach channel widths up to 160MHz and 2048 subcarriers per antenna.

CSI from each spatial stream were sampled at a rate ranging from 30Hz to 1.6kHz ($\mathbf{S_r}$ column), which directly affects their temporal resolution. Higher sampling rates imply finer temporal resolution, allowing more accurate capture of rapid changes in the environment and user activities.

However, the number of spatial streams and subcarriers and the sampling rate directly affect the collected data volume within a given observation interval. Consequently, real-time management of this data can become resource-intensive, requiring significant storage capacity and computing power. Finally, most datasets provide the complete CSI (FULL), including both amplitude and phase information. In contrast, others comprise only the amplitude (AMP) [68,74,80] or even only its preprocessed ($\overline{\text{AMP}}$) [81]. Typically, these data are stored in generic plain-text files (e.g., CSV or DAT format), which are obtained after minimal preprocessing of the collected raw data. In this regard, [91] is the only dataset that also provides raw CSI data in PCAP format (RAW).

In this context, the release of complete raw data becomes even more essential as scientific progress increasingly relies on access to large volumes of up-to-date, high-quality data.

Moreover, these datasets should be thoroughly documented and enriched with comprehensive information. For instance, only a few of the reported datasets provide details on the time period during which the data collection campaign occurred (**Time Coverage** column). Such information is essential for evaluating the long-term effectiveness and potential concept drift in developing CSIS solutions.

3.2. Cross-user diversification

Wireless signals encounter multiple environmental reflection surfaces, including walls, furniture, and human bodies, generating a complex mixture of propagation paths leading to *multipath components*. These components typically include both Line-of-Sight (LOS) and Non-line of Sight (NLOS) paths. The LOS component captures direct paths. In contrast, the NLOS component includes reflections caused by static components (e.g., walls, furniture, etc.) and dynamic components due to human movements and varying with the physical characteristics of the individual [18].

Therefore, to build robust and adaptable CSIS solutions, it is essential to diversify the CSI collected by involving a set of users with different characteristics, such as **gender** (⚥), **age** (🎂), and **physical attributes** (⚖), which may alter how Wi-Fi signals are reflected and scattered. For instance, age can influence movement speed, with younger people that tend to move more quickly than older ones. When movements are faster and more abrupt, the signal is scattered more randomly, causing quicker changes in phase differences [8]. Physical attributes (e.g., height, weight, and body shape) may alter how signals are scattered, reflected, or attenuated. Different body types cause distinct changes in CSI values, including phase shifts and the strength of multipath reflections [18,32].

For all these reasons, it is important to include information about the users in the description of the dataset.

User Heterogeneity in Public Dataset Using the key user characteristics identified above, Table 2 analyzes each dataset, focusing on the number of users (👥) and whether both men and women (⚥) of varying ages (🎂) and physical attributes (⚖), e.g., weight and height, were included. This information was extracted from the description in each paper or from the dataset webpage if explicitly provided.

As is evident, the scientific community has tried to incorporate as much diversity as possible among users during CSI data collection. However, while general agreement exists on considering key user characteristics, datasets have not been gathered following a standardized procedure. This inconsistency is particularly evident when comparing the number of users involved in each dataset. Specifically, most datasets included between 3 and 10 participants. Notably, [85] collected variations in CSI data from three human users as well as a medical bionic dummy. Beyond this, a small subset [69,76,82] relied on data from a single user. In contrast, 6 datasets involved a moderately larger number of users (i.e., up to 30), while only 2 involved many participants (i.e., from 60 to 100) [67,72].

However, many datasets did not fully account for participant characteristics during data collection. Specifically, gender was included in less than half of the cases [50,67,68,70,72,73,79,80,83,89,91], age was considered in about a third [65,66,72–75,79,87,89,91], and physical attributes were addressed in approximately half of the datasets [65–68,70,72,73,75,79,87,89–91]. Therefore, based on our findings, only a few datasets [72,73,89,91] incorporated all these factors simultaneously.

As for the level of detail in the user description, many datasets offer no information about participants [8,71,74,75,78,81,85,86,88]. Conversely, a significant portion provides only summary statistics [66,67,77,79,80], such as average weight or height and the total number of participants by gender. The remaining datasets offer detailed information [65,68,70,72,73,83,87,90], including attributes like gender, weight, and height for each individual user. Among these, Cominelli et al. [84] is the only one providing video recordings of each capture session as ground truth.

This analysis highlights the lack of uniformity in creating the datasets, underscoring the need for common methodologies. Such standardization would ensure that CSI datasets adequately capture user diversity and guide the development of effective methods for real-world applications. Accordingly, releasing detailed information about the users involved—without harming their privacy—is crucial for evaluating the robustness of CSIS methodologies across different users.

3.3. Cross-environmental diversification

The collected wireless signal is influenced by the physical environment used to test the specific task. Changes in the indoor elements, such as moving furniture or adding obstacles, can significantly affect the CSI measurements, thus impacting the effectiveness of sensing applications [93].

Consequently, data-driven CSI-based approaches that directly extract features from Wi-Fi signals and map them to human gestures may experience significant performance drops when applied in different environments. This makes developing generalizable solutions—that is, methods that continue to be effective when applied to new environments—particularly challenging.

A possible solution would be to collect data from heterogeneous environments. However, this approach is challenging since it requires considerable effort—each new environment introduces unique multipath effects, necessitating additional data collection and ground-truth labeling.

Alternatively, a general “one-size-fits-all” solution, in which the model is trained once and used everywhere (commonly found for applications such as image classification), is desirable [77]. To this aim, existing approaches follow two alternative paths. The first approach is to design domain-independent features less sensitive to environmental changes [79,83]. The second approach is to develop generalizable ML models that can operate effectively in different environments without extensive retraining [67,77].

In both cases, from the dataset viewpoint, it is crucial to have access to a wide range of heterogeneous environments to test the effectiveness of the proposed solutions.

Environmental Heterogeneity in Public Dataset In Table 2, we examine the publicly available datasets considering *(i)* the number of rooms in which data were collected (#), *(ii)* their layout (**Type**), and *(ii)* the presence (●) or absence (○) of additional obstacles beyond the basic perimeter structures like walls, ceilings, and floors (🪑)—i.e., common furniture of both work and home environments, such as desks, chairs, beds, etc..

Specifically, approximately half of the datasets were collected within a single environment [8,68,69,71,72,74,75,80,82,87,92,94], so they may be difficult to use when developing resilient approaches to environmental changes. In contrast, the remaining datasets seem better suited to achieve this goal. Among these, most were obtained by collecting data in 2 or 3 different environments [65,67,70,73,76–79,81,83–85,88,89,91], with the *FallDeFi* dataset [66] being the only one encompassing 5 environments.

Regarding the types of environments, the datasets include both residential settings—e.g., bedrooms, kitchens, and bathrooms—which typically involve smaller spaces, and workplace environments that range from small areas like laboratories and studios to medium and large spaces like halls, meeting rooms, classrooms, and seminar rooms. Since data collection is typically aimed at supporting projects undertaken by advanced research centers—e.g., companies or academic institutions—it is natural that most data collection has occurred in laboratories.

Furthermore, some datasets include empty rooms [70,89], while others include generic spaces that either do not fit into the previously mentioned categories or were not sufficiently detailed in the reference works [67–69,76,94].

Finally, most datasets involve CSI data collected in everyday environments that include typical obstacles like furniture, which helps to simulate realistic multipath effects (🪑). However, this does not hold for [8,69,82,90], where data collection was performed in controlled environments or LOS conditions, where the influence of typical household items and furniture was either minimized or completely absent.

3.4. ML-powered sensing tasks

The goal of CSI Sensing is to identify various human *tasks* related to multiple domains, such as healthcare, smart homes, security, human–computer interaction, and emergency response. Table 3 describes the main characteristics of the most popular CSIS tasks, listing the acronyms (**Acro**) used throughout this survey, the task type (**Task**), the recognition granularity (▼), multi-user involvement (👥), and a brief explanation of each (**Description**).

A large subset of such tasks falls under the Human Behavior Recognition (HBR), which considers the identification of everyday human behaviors in real-world contexts. HBR tasks are categorized into *fine-grained* and *coarse-grained* based on the granularity of movements composing a given action [75]. Coarse-grained activities encompass broader, whole-body movements that include significant changes in body position or the movement of multiple body parts simultaneously.

Fall Detection (FD) belongs to this category, in which the aim is to understand whether a person has fallen, typically treating it as a binary classification problem. Since falls can have several variations, including forward, backward, lateral, and positional falls, FD can be designed to identify the specific type of fall, making it a multiclass classification task. FD is especially important to ensure the safety of the elderly living independently [66].

Body Gestures Recognition (BG) has a finer granularity compared to FD, as it aims to perform more precise motion recognition. BG involves discerning among different whole-body motions, not just detecting falls. This includes recognizing various activities like walking, boxing, squatting, and other movements that require distinguishing between multiple actions, thus making it a multi-classification problem.

Typically, the above tasks involve detecting the motion of a single person within an environment. In contrast, *Human-to-Human Interaction Recognition (HHI)* focuses on recognizing movements that result from the interaction between at least two individuals. This makes the recognition task more challenging, as the system must discern and interpret the combined motions and interactions between multiple people [87]. HHI is crucial for applications to monitor group activities, analyze social interactions in diverse real-life scenarios, and develop smart environments.

Fine-grained activities typically involve small-scale movements, often limited to specific body parts like the hands or fingers (e.g., drawing shapes, pushing, hand swinging). *Hand Gestures Recognition (HG)* and *Sign Language Poses Recognition (SP)* are examples of typical fine-grained tasks. They aim to distinguish between subtle movements of specific body parts, necessitating precise detection and classification of multiple distinct gestures. Hence, they play a crucial role in human–computer interaction. In fact, they enable users to interact with applications without any physical control device, facilitating use in virtual reality systems, smart home control, and sign language recognition [25].

In particular, SP focuses on detecting subtle differences in finger positions and hand movements, which makes it highly challenging [65]. This difficulty is due to the vast number of gestures, their similarities, and the complexity involving coordinated movements of the head, arms, hands, and fingers. Capturing these minute variations makes it the most intricate form of HBR.

Other sensing tasks do not fall under the HBR category, extending the application of CSI to other purposes. They focus on aspects such as localization, identification, and awareness of the environment. In particular, *Copresence Detection (CD)* (a.k.a. Occupancy Detection) involves determining whether a person is present in a particular area or not. Thus, it is crucial for security applications (e.g., detecting unauthorized access), energy efficiency (e.g., controlling lighting and electrical appliances), and as a trigger for other sensing applications (e.g., opening/closing doors or lighting up/down environments automatically).

On the other hand, *Human Identification (HID)* and *Biometrics Estimation (BE)* aim to derive fingerprinting models based on the unique way people affect wireless signals. Specifically, HID focuses on recognizing specific individuals, and it is essential for improving security (e.g., for access control and physical intrusion detection) and enhancing user convenience in smart homes (e.g., customizing settings based on people). Conversely, BE involves estimating the physiological characteristics of individuals (e.g., body fat rate, muscle mass, water content, and bone density). Notably, BE becomes a fine-grained task when leveraging wireless signals to detect heartbeat or respiration rates, as these internal physiological signals demand capturing extremely subtle CSI variations. It is particularly useful in health monitoring, fitness assessments, and personalized wellness programs [68].

Other tasks, such as *Indoor Localization (IL)*, aim to detect the location of people inside a building without the aid of a positioning device. This is achieved by analyzing the perturbations they cause in specific parts of the environment. Specifically, IL can be applied to locate a single person—viz. *User Localization (UL)*—or to determine the positions of a group of people—viz. *Crowd Localization (CL)*. IL tasks are essential for applications such as navigation assistance, context-aware services, and enhancing smart home automation [81]. These tasks differ according to the precision of localization. Therefore, they can be approached as a classification problem—i.e., identifying predefined zones—or as a regression problem—through precise Cartesian localization.

Finally, *People Counting (PC)* and *Walking Velocity Estimation (WVE)* are other regression problems. Specifically, *PC* involves estimating the number of people in a specific area. It can help manage crowd flow in public spaces, optimize resource allocation in retail environments, and ensure safety by monitoring occupancy levels during events or emergencies [95]. Conversely, *WVE* focuses on determining the speed and direction of a person walking within indoor environments. One

Table 3
CSI sensing tasks.

Name	Acro	Task		▼	👥	Description
		©	®			
Biometrics Estimation	BE	○	●	⊕	○	Infers internal physiological signals (e.g., heartbeat, respiration) from extremely subtle motion or body attributes (e.g., body fat rate, muscle mass, water content)
Bogy Gestures Recognition	BG	●	○	⊖	○	Recognition of full-body activities (e.g., walking, boxing, squatting) in single individuals
Copresence Detection	CD	●	●	—	○	Determines whether a room or area is occupied (at least one person) or empty (viz. *binary*)
Crowd Localization	CL	●	●	—	●	Locates group of people indoors by either identifying its location into predefined zones (viz. *classification*) or estimating its precise coordinates (viz. *regression*)
Fall Detection	FD	●	○	⊖	○	Determines whether a fall has occurred (viz. *binary* case) or identifying the specific type of fall (viz. *multi-class* case)
Hand Gestures Recognition	HG	●	○	⊕	○	Recognition of subtle movements of hands/fingers (e.g., waving, pinching, drawing shapes)
Human-to-Human Interaction Recognition	HHI	●	○	⊖	●	Recognizes movement arising from the active interaction of at least two people
Human Identification	HID	●	○	—	○	Recognizes unique individuals
People Counting	PC	○	●	—	●	Estimates how many people are in a given indoor environment
Sign Language Poses Recognition	SP	●	○	⊕	○	Recognition of complex finger, hand, and arm configurations used in sign languages
User Localization	UL	○	●	—	○	Locates a person indoors by estimating its precise coordinates
Walking Velocity Estimation	WVE	○	●	—	○	Determines the walking speed of a person and possibly his direction

Task: Classification (©), ®: Regression (®). *Multi-user* (👥): Task involving a single user (○), task involving multiple users simultaneously (●). *HBR Task Granularity* (▼): Fine-grained task (⊕), Coarse-grained task (⊖), Not a HBR task (—).

possible application of WVE is passive monitoring in smart homes, healthcare facilities, and industrial environments.

WiFi Sensing Tasks in Public Datasets Table 2 outlines each dataset based on the CSIS task enabled (**GT** column) and the number of classes (# column) in the specific case of classification tasks. For PC, this column specifies the maximum number of people involved.

Most datasets focus on HBR, the majority of which provide information on body gestures (BG). Typically, these datasets include a limited number of body gestures, usually around 6 [8,71,78,80,88] or 7 [74,76,90], with a maximum of 16 gestures [70]. However, [67] stands out by including a significantly larger set of 40 gestures, providing a more comprehensive resource for gesture recognition tasks.

A notable portion of the datasets focuses on HG [69,75,77,79], but featuring only between 5 [75] and 10 [79] distinct hand gestures. FD tasks is addressed in three datasets [66,68,85]. Although [68] focuses on detecting whether a fall has occurred (i.e., only two classes corresponding to fall or non-fall), it uniquely collects data from five distinct locations to improve generalization. In contrast, [66] offers a broader ground truth, classifying falls into four distinct categories.

Similarly, for SP, [65] and [68] focus on pose recognition in sign language and fine-grained finger sign detection, respectively. [65] includes a comprehensive set of 276 signs, while [68] targets a more specific task with 10 distinct finger positions. In addition, [72,87] deal with HHI, providing information on 12 and 17 types of interactions, respectively.

WiMANS [89], in contrast to the other datasets where the data represent a single user engaging in specific activities within an environment, provides the ground truth by capturing the movements of a target user while other users are simultaneously present in the acquisition environment without interacting with it. In contrast, other datasets [72,78,81,87] are specifically designed to capture CSI data when multiple users are actively interacting. These works focus on human-to-human interaction or group activities rather than observing the movement of an individual in the presence of others.

The remaining datasets capture information regarding the identifier of a person (HID), its physical attributes (BE), the location of one (UL) or more people (CL), or the number of people in a room (PC). Among them, [68,78,80,81,91,92] focus on PC and HID, involving up to 10 and 30 people, respectively. Conversely, [69,78,81,82] aim to address UL and CL tasks, respectively. Specifically, depending on the predefined task, [81] supplies information about the particular area within a room where a group of people are located rather than providing the exact location of an individual user.

Lastly, [68] is the only one providing information about body fat, muscle, water, and bone rate of people involved (BE).

3.5. Data release

Finally, the public release of a dataset involves making the collected data accessible to the broad research community, following one of the UNESCO principles for open knowledge. Datasets must be **well-documented and structured** to ensure usability, **clearly licensed** to specify permitted uses, and **hosted on reliable platforms** to ensure long-term availability.

As reported in Table 2 (see **Plat.** column), datasets are hosted across a variety of platforms, some of which are specifically designed to facilitate sharing, accessibility, and usability. This is the case of **4TU.ResearchData** (☼) [71], **Dataport** (◆) [79,92], **Figshare** (◎) [76,78], **Kaggle** (k) [89], **Mendeley** (■) [72], **Research Data Unipd** (■) [83], **Sensing Dataset Platform** (∞) [85], and **Zenodo** (Z) [82,84,91]. These platforms are crucial in advancing open science by providing essential features like discoverability, standardized citation formats

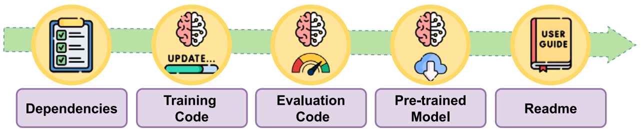

Fig. 3. Key aspects of the *Research Code Release Guidelines.*

with metadata and permanent identifiers (e.g., Digital Object Identifier (DOI)), and long-term availability, making them ideal for academic and research contexts.

Among these platforms, although Kaggle was initially launched as a platform for sharing data for competitions in the ML community, it has grown to become a versatile and widely recognized resource for sharing datasets.

Despite the different services offered by these specific platforms, our findings reveal that personal storage platforms, such as **Box** (box) [65], **Baidu** (🐾) [77,90], **Drive** (△) [8,69,74,75,80], **DropBox** [87], **GitHub** (🐱) [68,70,73,81,88], and **Mega** (M) [66] have been preferred in most cases for dataset sharing.

However, these platforms are not explicitly designed for this purpose and have some limitations. Specifically, they lack critical features like discoverability and standardized citation support, which are essential for academic and research use. Furthermore, their long-term availability is uncertain, as control over the data rests solely with the owner.

Similarly, GitHub, often employed to host datasets alongside code, is constrained by limited storage capacity and its primary focus on software development rather than dataset archiving.

In one isolated case, the dataset is accessible only by **explicit request** via e-mail (✉) [67], reflecting a controlled approach to data sharing, often driven by privacy concerns or the sensitive nature of the data. However, this approach has substantial limitations that cause researchers to face significant challenges as early as data access and processing. These challenges include, for instance, a lack of prior knowledge of the content or format of the data, and a lack of assurance that the data will be provided or remain accessible when requested.

4. Code availability and reproducibility

For the experimental reproducibility, we consider the two key requirements already discussed: **Open Data** and **Open Source Code**. We report all works that, to the best of our knowledge, meet at least one of the two requirements. When the code is not publicly available, but the data are accessible, ensuring full reproducibility requires a complete and detailed description of the proposed methodology and the entire experimental setup. This would enable other researchers to replicate the evaluation workflow "from scratch". Conversely, if only the code is available, it becomes impossible to reproduce the specific experimental campaign as originally conducted. However, the code can still be utilized to evaluate the generalizability of the proposed methodology across different datasets and scenarios.

In analyzing the code availability, we consider the key components described in the *Research Code Release Guidelines* [96] provided for the ML community publishing at NeurIPS and summarized in Fig. 3.

4.1. Open data

In Table 4 (column **Dataset**), we list the names of the datasets employed by each work (**Name**) and specify their availability (**Open**): fully available (✅), partially available (☑), or unavailable (⊗). Additionally, we indicate the sensing tasks addressed (**CSI Task**), whether pre-processed data (**Pre-proc**) is provided (✅) alongside the raw data or not (⊗). Pre-processing typically involves transformative operations—e.g., de-noising, filtering, spectrogram extraction, or converting CSI into different formats, such as images—that modify the raw CSI data to enhance its usability for data-driven models. We also highlight works that do not need to release pre-processed data because, by applying only standard operations such as normalization and data segmentation, they do not perform pre-processing as defined above (**—**).

Most of the work mainly uses fully open datasets, thus moving toward the potential full reproducibility. Conversely, a smaller subset of works [94,100,101,103,104,106,109,111,112,116,119,120,122,124,125] has employed both public datasets and privately collected data, resulting in only partial reproducibility. Lastly, a limited number of works [95,97,98,115] have relied solely on private datasets, making exact replication infeasible.

Among public datasets, UT-HAR [8,94,100,101,103,105,106,108,110,112–114,117,119,125] and Widar3.0 [77,79,102,107,111–114,116,119–123] are the most widely used. Specifically, UT-HAR Widar3.0 are commonly employed for BG and HG tasks, respectively, which also results in the most addressed CSIS tasks. Other datasets, such as ARIL, FallDeFi, and SignFi, are employed in studies that, in turn, focus on tasks like HG [69,77,118,121], FD [66,85,99,106], and SP [99,104,109,114,118,119], respectively. Finally, only a very limited subset of works performing pre-processing operations also provide pre-processed data [66,75,79,81,83,84,107].

4.2. Open source code

In Table 4 (column **Source Code**), we analyze each work referring to the Research Code Release Guidelines [96]. In particular, we assess the completeness of the ML code by inspecting the following key aspects: *Dependencies*, *Training Code*, *Evaluation Code*, *Readme*, and *Pre-trained Models*.

Dependencies (Dep.) refers to the presence of a `requirements.txt` file or equivalent, along with clear instructions for installing all necessary dependencies. Precisely defining dependencies is essential for replicating the experimental environment and avoiding compatibility issues that could impact model performance and reproducibility. Accordingly, we indicate whether a complete list with exact package versions is provided (✅), only some dependencies are specified while others remain undefined (☑), or if version information is absent (⊗).

Table 4 shows that the availability of precise dependencies varies across different works. Specifically, a subset of works provides the complete list of dependencies [66,68,74,76,80,83,84,89,112,113,115,123], along with the exact version of all required packages, while another subset only partially defines their dependencies [69,75,77,97–99,103]. However, a noticeable portion of the works do not provide any information on their dependencies [8,67,81,88,90,95,107,111,119,121], making it difficult to replicate the original experimental environment and leading to possible compatibility problems when attempting to use such code.

Training Code (Train.), pertains to the availability of code for training the ML or DL model and reproducing the results of the paper. This code should also provide detailed descriptions of all hyperparameters, including the values used by default and those allowed when trying different configurations (**T.Doc.**). To this end, hyperparameters should not be "hardcoded" within the script, as in [8,66,79,97,123], for example. Still, they should be easily adjustable through configuration files or command-line arguments to simplify reproducibility and flexibility.

As reported, all works releasing their code also include the necessary script for training ML/DL models. However, it is worth noting that only a subset also provides a detailed description of how to use the code, including a description of input parameters and configuration options [75,77,83,84,89,99,103,107,112,113,115,121,123]. For the other works, this lack can hinder usability and make it more challenging for other researchers to adapt the code for further experimentation.

Additionally, some works [8,69,74,75,79,80,90,103,107,115,119,121] provide training code exclusively for their proposed method (☑),

Table 4
Publicly available code for CSI Sensing.

Year	Work	Dataset				Source code								
		Name	CSI Task	Open	PData	Fwk.	Dep.	Train.	T.Doc.	Eval.	E.Doc.	PMod	Readme	Rep.
2017	[8]	UT-HAR	BG	✅	❌	TF	❌	☑	❌	✅	❌	❌	☑	🐙
2018	[66]	FallDeFi	FD	✅	✅	▲	✅	✅	❌	☑	❌	❌	❌	🐙
	[97]	Private	HG	❌	❌	🔥	☑	✅	❌	☑	❌	❌	❌	🐙
	[67]	Zhang18	BG	✅	❌	learn	❌	✅†	❌	✅	❌	❌	❌	🐙
	[68]	Wang18	HID, SP, FD, BE	✅	—	🔥	✅	✅	❌	✅	✅	✅	☑	🐙
	[98]	Private	UID	❌	❌	TF	☑	✅	❌	✅	❌	❌	☑ 📖	🐙
2019	[69]	ARIL	HG ×UL	✅	—	🔥	☑	☑	❌	☑	❌	✅	☑	🐙
	[99]	SignFi FallDeFi	SP FD	✅	—	TF	☑	✅	✅	✅	✅	❌	☑	🐙
	[100]	UT-HAR Private	BG	☑	❌	-	-	-	-	-	-	-	-	-
2020	[101]	UT-HAR Private	BG	☑	❌	–	–	–	–	–	–	–	–	-
	[102]	Widar3.0	HG	✅	❌	-	-	-	-	-	-	-	-	-
2021	[75]	Xiao21	BG, HG	✅	✅	TF	☑	☑	✅	✅	✅	✅	✅	🐙
	[103]	UT-HAR Private	BG	☑	❌	🔥	☑	☑	✅	☑	❌	❌	❌	🐙
	[104]	SignFi Private	SP BG	☑	—	–	–	–	–	–	–	–	–	-
	[105]	UT-HAR	BG	✅	❌	-	-	-	-	-	-	-	-	-
	[74]	CSI-HAR	BG	✅	—	TF	✅	☑	❌	✅	❌	❌	☑	🐙
	[106]	UT-HAR FallDeFi Private	BG FD BG	☑	—	-	-	-	-	-	-	-	-	-
2022	[76]	Zhuravchak22	BG	✅	❌	🔥	✅	✅	❌	✅	❌	❌	☑ 📖	🐙
	[79]	Widar3.0	HG	✅	✅	TF	❌	☑	❌	☑	❌	❌	❌	◆
	[107]	Widar3.0	HG	✅	✅	🔥	❌	☑	✅	☑	❌	❌	❌	🐙
	[77]	Widar3.0 ARIL CSIDA	HG	✅	❌	🔥	☑	✅	✅	✅	❌	❌	☑	🐙
	[80]	NTU-Fi-HAR NTU-Fi-HID	BG HID	✅	—	🔥	✅	☑	❌	☑	❌	❌	☑	🐙
	[108]	UT-HAR	BG	✅	❌	-	-	-	-	-	-	-	-	-
	[109]	SignFi Private	BG	☑	❌	–	–	–	–	–	–	–	–	-
	[81]	Choi22	PC, CL	✅	✅	learn TF	❌	✅	❌	✅	❌	❌	☑ 📖	🐙
	[82]	AntiSense	UL	✅	—	TF	✅	✅	❌	☑	✅	❌	✅	🐙

(continued on next page)

Table 4 (*continued*).

Year	Work	Dataset				Source code								
		Name	CSI Task	Open	PData	Fwk.	Dep.	Train.	T.Doc.	Eval.	E.Doc.	PMod	Readme	Rep.
2023	[110]	UT-HAR Alazrai20	BGHHI	✅	❌	-	-	-	-	-	-	-	-	-
	[111]	SAR WiAR Widar3.0 Private	BGBGHGBG	🟡	❌	✣	❌	🟡	❌	🟡	❌	❌	❌	🐙
	[83]	Meneghello23	BG	✅	✅	🔶	✅	✅	✅	✅	✅	✅	✅	🐙
	[84]	Cominelli23	BG	✅	❌	🔶	✅	✅	✅	✅	✅	❌	✅	🐙
	[112]	UT-HAR Widar3.0 Private	BGHGBG/HID	🟡	▬	🔥	❌	❌	❌	❌	❌	❌	❌	🐙
	[113]	UT-HAR Widar3.0 NTU-Fi-HAR NTU-Fi-HID	BGHGBG HID	✅	▬	🔥	✅	✅	✅	✅	✅	✅	✅	🐙
	[114]	UT-HAR Widar3.0 SignFi	BGHGSP	✅	❌	🔥	✅	✅	❌	❌	❌	❌	❌	🐙
	[115]	Private	HID	❌	❌	🔥	✅	🟡	✅	✅	✅	❌	🟡	🐙
	[85]	FallDar FallDeFi	FD	❌	❌	-	-	-	-	-	-	-	-	-
2024	[116]	Widar3.0 Private	HGBG	🟡	❌	–	–	–	–	–	–	–	–	-
	[94]	UT-HAR Private	BG	🟡	❌	-	-	-	-	-	-	-	-	-
	[117]	UT-HAR NTU-Fi-HAR NTU-Fi-HID	BGBGHID	✅	❌	–	–	–	–	–	–	–	–	-
	[118]	CSI-HAR SignFi ARIL	BGSPHG	✅	▬	-	-	-	-	-	-	-	-	-
	[119]	UT-HAR Widar3.0 SignFi Private	BGHGSPHG	🟡	▬	🔶	❌	🟡	❌	✅	❌	❌	🟡	🐙
	[120]	Widar3.0 Private	HGBG	🟡	❌	-	-	-	-	-	-	-	-	-
	[121]	Widar3.0 CSIDA ARIL	HG	✅	❌	🔥	❌	🟡	✅	✅	❌	❌	❌	🐙
	[122]	Widar3.0 Private	HG	🟡	▬	-	-	-	-	-	-	-	-	-
	[123]	FallDar OPERAnet Widar3.0	FDBGHG	✅	❌	🔥	✅	✅	❌	🟡	❌	❌	🟡	🐙
	[95]	Private	WVE	❌	❌	▲	❌		❌		❌	❌	❌	🐙
	[124]	CSLOS Private	BG	🟡	▬	–	–	–	–	–	–	–	–	-
	[88]	WiSense	BG	✅	❌	▲	❌	✅	❌	✅	❌	❌	❌	🐙
	[125]	UT-HAR Private	BG	🟡	❌	–	–	–	–	–	–	–	–	-
	[89]	WiMANS	HID/UL/BG	✅	▬	🔥	✅	✅	✅	✅	✅	❌	✅	🐙
	[92]	Bian24	HID	✅	❌	–	–	–	–	–	–	–	–	🐙
	[90]	CP-HAR	BG	✅	▬	🔶	❌	🟡	❌	✅	❌	❌	🟡	🐙

Open Data: Available (✅), Partially Available (🟡), Unavailable (❌);
Pre-processed Data (PData): Provided (✅), Not Provided (❌), Not Required (▬);
ML/DL Framework (Fwk.): MATLAB (▲), Scikit-learn (●), PaddlePaddle (✣), PyTorch (🔥), Keras/TensorFlow (🔶);
Dependencies (Dep.): Fully Specified (✅), Partially Specified (🟡), Not Provided (❌);
Training Code (Train.): Fully Available (✅), Only Proposal (🟡), Not Provided (❌);
Evaluation Code (Eval.): Fully Available (✅), Partially Available (🟡), Not Provided (❌);
README: Detailed (✅), Minimal (🟡), Absent (❌), Jupyter Notebook Available (📖);
Pre-trained Model (PMod.): Provided (✅), Not Provided (❌);
Code Repository (Rep.): GitHub (🐙), IEEE DataPort (◆).

omitting the implementation needed to train and evaluate the baselines (i.e., state-of-the-art methods) used for comparison.

For a fair comparison, the proposed approach and the baseline should be trained and evaluated using the same data and under identical experimental conditions. However, relying on separate implementations for training baselines can introduce inconsistencies (e.g., variations in pre-processing, hyperparameter settings, or evaluation criteria), potentially leading to biased results. Since state-of-the-art implementations often originate from different sources, controlling experimental conditions becomes more complex. As a result, any discrepancies introduced, even if unintentional, may lead to unfair performance comparisons, making it challenging to draw definitive conclusions.

It is worth noting that some works release incomplete code, even related to their own proposed methods. Specifically, [67] provides code for running experiments with ML models used for comparison rather than the proposed method (viz. "CrossSense"), which, in contrast, is a deep neural network based on Multi-Layer Perceptron (MLP). Similarly, [92] provides only the code for data pre-processing, including the train-test split, without including the training and evaluation code. Conversely, [114] adapts the code designed for Computer Vision (CV) tasks (e.g., image classification) to handle CSI data. However, the authors did not release the modified version of the code. As a result, since only the original CV-based implementation is available, applying it directly to CSI tasks becomes challenging.

Evaluation Code (Eval.) refers to the availability of the exact code used for experimental evaluation, ensuring the reproducibility of the results as reported in the reference paper. The code should be accompanied by a detailed description of the evaluation procedure, including all necessary operations from model evaluation to processing and visualization of the corresponding results (**E.Doc.**).

The availability of evaluation codes varies significantly among the analyzed works. Specifically, some works provide a comprehensive evaluation framework that allows for the complete reproduction of outcomes presented in the corresponding manuscripts [8,67,68,74–77,81,84,88,90,98,113,115,119]. In contrast, other studies only include partial evaluation code [66,69,79,80,82,97,103,107,111,123], which typically provides basic performance metrics—e.g., mean accuracy, loss/accuracy trend across training epochs, confusion matrix—but it omits essential post-processing steps necessary for detailed result inspections. Therefore, the absence of a complete evaluation code requires extra effort to replicate the experimental workflow and validate its findings fully.

Pre-trained Models (PTMod) refers to the release of pre-trained models to validate the final results. The release of pre-trained models is valuable for supporting scientific research as they can be adapted (viz. fine-tuned) to address new tasks. This may help reduce computational costs and facilitate further experimentation.

As observed, only a small number of works have released pre-trained models [68,69,75,83], indicating that this practice remains uncommon in the CSIS domain.

Finally, to further enrich our analysis, we indicate the framework (**Fwk.**) utilized to implement the ML and DL methods. Additionally, we include links to the corresponding code repositories (**Repo.**) to facilitate access.

Readme concerns the availability of a comprehensive `README` file that ideally includes precise commands and step-by-step instructions necessary to replicate the experimental workflow and produce the final results reported in the paper. It should encompass a description of *(i)* the installation procedure for the required dependencies, *(ii)* an overview of the repository organization with guidelines for *(iii)* data pre-processing, as well as instructions for *(iv)* training and *(v)* evaluating the models, including post-processing and visualization of the results. Furthermore, it should include *(vi)* practical examples demonstrating how to run the provided scripts, ensuring usability and full reproducibility.

Notably, only a few papers provide instructions for replicating experiments with varying levels of detail. Specifically, [8,68,69,74,76,77,80,81,90,97,115,119,123] offer only *minimal* instructions (✓), typically including basic information such as the script required for training or evaluation and, in some cases, only a description of the organization of the repository content. Conversely, [75,83,84,89,99,113] provide *step-by-step* guides (✓), offering more structured and comprehensive instructions to facilitate reproducibility.

Although [76,81,98] provide only minimal instructions, they supplement it with *Jupyter Notebooks* (📖) that facilitate replicating the experimental workflow (see jupyter.org). Even if "notebooks" are valuable tools for visualizing intermediate results and guiding users through the workflow, proper annotation is essential to facilitate their use without unnecessary effort. Thus, despite the improved usability, comprehensive documentation remains crucial for ensuring full reproducibility.

4.3. Model architectures and reproducibility effort

The adopted model represents the core of any learning-based approach, and the model *class* employed in CSI-based sensing does have implications for reproducibility. Beyond the availability of code and data, reproducibility vary according to the *type and intrinsic complexity* of the adopted model. Accordingly, we provide an overview of the main model classes employed in CSIS, qualitatively assessing their complexity and expected effort to reproduce training and inference pipelines. Rather than detailing each model, which is impractical, we map the CSI-based sensing approaches onto broad classes and estimate the effort that may be required to reproduce the method propose is enough data and details are available. A quantitative complexity analysis (e.g., parameter number, FLOPs, training/inference time) is outside our scope, as such metrics are seldom reported, and no standardized benchmarks exist. Moreover, model configurations are highly dataset-dependent (e.g., the number of subcarriers and antennas) and influenced by hardware and implementation choices, making direct comparisons impractical.

To provide a consistent view across works, we adopt a qualitative complexity criterion that considers both architectural and practical factors. From an architectural perspective, complexity increases with model depth and end-to-end connectivity—e.g., shallow MLP or Convolutional Neural Network (CNN) compared to deeper or multi-branch networks such as Residual Network (ResNet) and InceptionNet. From a practical viewpoint, the reproducibility effort increases with the complexity of the data pre-processing pipeline (e.g., image-like CSI representations), hardware requirements (e.g., CPU or GPU), hyperparameter sensitivity, and overall setup difficulty.

Table 5 summarizes the representative models identified in the surveyed works, grouped by model family and sub-category. Notably, we focus only on works that publicly release both model implementations and training code (see Section 4). We believe this mapping also provides practical guidance on locating the released implementations, thereby supporting reproducible research

As shown, the surveyed works cover a broad range of models, reflecting heterogeneous reproducibility needs. Specifically, classical ML models—e.g., Support Vector Machine (SVM) [66,67,81] or Random Forest Classifier (RFC) [66,67,81]—present the lowest reproducibility effort, as they are typically implemented in standard libraries such as `scikit-learn`, require no specialized hardware, and are less sensitive to hyperparameter tuning.

Unlike classical ML models, DL approaches typically require *GPU acceleration* to handle their higher computational complexity, which may not always be available, especially on resource-constrained edge devices. Moreover, while these models benefit from mature frameworks such as `TensorFlow` and `PyTorch`, which provide fine-grained control over architecture design and training, their use generally demands greater technical expertise and setup effort.

Table 5

Models employed in reproducible CSI-based sensing, grouped by family and sub-category. The table highlights representative models with publicly available implementations and training code. Different colors are used to distinguish between Classical ML and DL models.

Base model		Papers	Complexity
Family	Sub-category		
Classical ML	SVM	[66,67,81]	○○○
	k-NN	[67]	
	NB	[66,67]	
	LR	[66,81]	
	RFC	[66,67,81]	
	Boosting	[67,81]	
Shallow DL	MLP	[81,113]	●○○
CNN	1D-CNN/2D-CNN	[74–76,82,98,111–113]	●●○
	LeNet	[97]	
	C-CNN	[114]	
RNN	Bi-LSTM/A-BLSTM	[74,113]	●●○
	GRU	[113]	
	LSTM	[8,74,76,113,115]	
	CNN+RNN	[79,113]	
Deep CNN	AlexNet	[68]	●●●
	VGG	[68]	
	Inception	[68,76,83,84]	
	ResNet	[68,69,77,107,113–115,121]	
Generative	GAN	[99]	●●●
	VQ-VAE	[80]	
Transformer	ViT	[113,114]	●●●
	Custom Self-Attention	[103]	
	CapsNet	[119]	

Architecture: Bidirectional Long Short-Term Memory (Bi-LSTM), Capsule Network (CapsNet), CasualNet (C-CNN), Convolutional Neural Network (CNN), Gated Recurrent Unit (GRU), Generative Adversarial Network (GAN), Logistic Regression (LR), Long Short-Term Memory (LSTM), Multi Layer Perceptron (MLP), Naive Bayes (NB), Random Forest Classifier (RFC), Recurrent Neural Network (RNN), Residual Network (ResNet), Support Vector Machine (SVM), Vector Quantized Variational Autoencoder (VQ-VAE), Vision Transformer (ViT), Visual Geometry Group (VGG), k-Nearest Neighbors (**k-NN**). *Boosting* includes AdaBoost, Light Gradient Boosting Machine (LGBM), and Extreme Gradient Boosting (XGBoost). *Inception* includes InceptionNet and InceptionTime. *Complexity*: Low (○○○), Low-Medium (●○○), Medium (●●○), High (●●●).

This growing shift toward DL architectures, despite the higher complexity, stems from their enhanced ability to extract information from CSI data. This trend is driven by the observation that CSI in MIMO systems exhibits spatial and temporal patterns similar to those found in images or sequential data. Hence, researchers have widely borrowed models originally developed in other domains, such as CV (e.g., CNN) and Natural Language Processing (NLP) (e.g., Transformer-based architectures).

These range from shallow CNN variants—e.g., 1D/2D-CNN [74–76,82,98,111–113] and LeNet [97]—and deeper and more sophisticated architectures such as ResNet [68,69,77,107,113–115,121], Inception [68,76,83,84], and Visual Geometry Group (VGG) [68]. Similarly, Recurrent Neural Network (RNN)—e.g., Long Short-Term Memory (LSTM) [8,74,76,113,115] and Gated Recurrent Unit (GRU) [113]—are also used to capture temporal dependencies in CSI sequences.

Complexity further increases with hybrid, multi-view, and fusion models that combine different components—e.g., CNN+RNN [79,113] or CNN+Self-Attention [103]—and process either distinct views of the same CSI data (e.g., temporal vs. channel) or data from different sources (e.g., CSI and video [115]).

Finally, advanced *Transformer*-based—e.g., Vision Transformer (ViT) [113,114]—and *Generative* models—e.g., Generative Adversarial Network (GAN) [99] or Vector Quantized Variational Autoencoder(VQ-VAE) [80]—introduce additional training and tuning challenges, often relying on *adversarial* or *self-supervised learning* procedures. Hence, while these approaches push the limits of model performance, they also widen the gap between advanced model design and deployability on resource-constrained edge devices.

5. Open issues and challenges

This survey focuses on a particular class of ISAC operations, namely *passive* and *indoor* sensing, in which the user is, in general, a room occupant and does not actively participate in the sensing process via specific devices (e.g., smartwatches or smartphones) or software applications. Accordingly, this section outlines the key challenges and open issues that we deem most relevant for the advancement and practical deployment of such ISAC systems.

5.1. Lack of standardization and benchmarking

One of the most pressing challenges is the absence of standardized protocols for data collection, processing, and evaluation. As shown in the previous sections, existing CSI-based datasets vary significantly in format, hardware, and experimental setup. This heterogeneity hinders reproducibility and complicates direct comparisons between different algorithms, especially when some leverage temporal dynamics of CSIs while others focus on static representations. Furthermore, performance metrics and evaluation tasks are not uniformly defined across the literature, making it difficult to assess progress in the field. Efforts toward standardized benchmarking datasets, a unified taxonomy, and evaluation protocols would greatly benefit the community.

5.2. Environmental robustness and generalization

A core limitation of many existing models is their sensitivity to environmental changes. Small variations in the spatial configuration, furniture, or human presence can significantly degrade performance.

Hence, the development of models that are robust to such environmental dynamics remains a critical open issue. Research in transfer learning and domain adaptation [126,127] shows promise for generalizing across domains, but further work is needed to make these approaches viable in real-time applications.

Moreover, CSI measurements are inherently noisy and subject to various sources of interference, like multipath effects and device imperfections. This often leads to models that perform well only under tightly controlled conditions. Improved preprocessing methods, robust feature extraction, and denoising techniques are crucial to building reliable sensing systems [128].

Finally, most current CSI-based sensing systems are designed for single-user environments. However, real-world applications—such as smart homes, public spaces, or factories—often involve multiple occupants whose activities may overlap in time and space. Multi-person sensing remains a major challenge due to complex signal interference and ambiguous spatial signatures [129]. New approaches capable of disaggregating and interpreting many concurrent signal patterns are needed.

5.3. Ethical and privacy considerations

As Wi-Fi sensing systems become more accurate and unobtrusive, privacy concerns become increasingly critical. Unlike classical vision-based sensing (e.g., camera-based smart surveillance), which requires LOS and can be easily obstructed, Wi-Fi can operate through walls and other barriers [19], raising ethical concerns around surveillance, consent, and data ownership. The ability of CSI to capture detailed fingerprints of the environment and its occupants—enabling learning-based models to successfully tackle a wide range of tasks, often passively and without the user's awareness or consent—creates a fundamental tension between sensing capabilities and privacy.

This topic has been discussed in recent literature [82], and opens an interesting research area on how to guarantee legitimate sensing while blocking attacks or simply unauthorized use of the information embedded in CSIs.

Obviously, there is also an ethical and privacy issue related to published databases and released, but this aspect goes beyond the scope of this paper. It is common to all datasets and code that involves human activities and should be addressed at the level of the platforms, like Zenodo or GitHub, that foster and support permanent data and code public access. This highlights the importance of integrating stronger privacy-preserving mechanisms like Differential Privacy (DP), which provides formal, measurable privacy guarantees by adding calibrated statistical noise to the data, which provably limits the ability to infer information about any single individual [130].

5.4. Real-time and edge deployment

Although many proposed systems leverage deep learning architectures (often inspired or adapted from computer vision), their computational complexity limits real-time deployment on resource-constrained edge devices. The development of lightweight models optimized for low-latency and low-power inference, like TinyML, is key for practical applications in smart homes and Internet of Things (IoT) systems [131]. In contrast to purely data-driven methods, hybrid approaches combining model-based insights (e.g., Fresnel zone theory) with learning-based inference may offer more interpretable and efficient alternatives.

5.5. Sensing with reconfigurable intelligent surfaces

Recently, new methods for introducing controllable multipath into the radio environment have been explored using Reflective Intelligent Surfaces (RIS). These surfaces are composed of many sub-wavelength elements that can assume different configurations to control how radio waves are reflected or scattered by adjusting the phase, amplitude, and polarization of the impinging waveforms [132]. The capability to programmatically alter propagation within an environment has several consequences for CSI-based sensing.

First, different RIS configurations can significantly alter the fading characteristics—and consequently the CSI—observed by the receivers, even when there are no physical variations within the room. In this case, trained sensing models may underperform in a given environment if they do not take into account the RIS-induced modifications, thereby amplifying the generalization challenges highlighted in Section 5.2.

Second, the impact of RIS on sensing can be studied from two opposite perspectives. On the one hand, the effects of RIS-induced channel variations can be treated as "noise" to be removed to identify domain-invariant features. In addition, when used to deliberately modify the signal, RIS can serve as an effective privacy countermeasure by actively obfuscating the CSI to prevent unauthorized sensing [133]. On the other hand, a RIS in the environment provides an opportunity to improve sensing performance when it is co-designed with the sensing system [134]. Therefore, using a RIS to control propagation within an environment can either enhance or worsen privacy, creating new potential attack surfaces.

Finally, there is one crucial consideration about the reproducibility of sensing results when a RIS is deployed. To ensure the experimental results are meaningful, reproducible, and comparable, datasets that include measures from RIS-enabled environments should also record and include appropriate metadata for the different RIS configurations.

5.6. Future directions and opportunities

Several research avenues have recently emerged with significant potential:

- Hybrid Sensing Technologies: Combining CSI from Wi-Fi communications with other technologies in different bandwidths, such as Long Range (LoRa), millimeter Wave (mmWave), or RFID, can enhance robustness and enable more powerful sensing capabilities [135].
- Feature Transfer and Domain-Invariant Representations: Developing signal representations invariant to domain changes (like micro-Doppler effects [83]) could improve generalization across environments and user conditions.
- Generative Models and Synthetic Data: Generative Artificial Intelligence (GenAI) techniques and diffusion models could be used to augment datasets, simulate edge cases, or provide analytic insights into signal properties [136].
- eXplainable Artificial Intelligence (XAI) for Wi-Fi Sensing: Black-box ISAC models remain challenging to interpret. Applying XAI methods [137] could improve trust, debugging, and understanding of how features are extracted from CSI.
- Language-Inspired Signal Modeling: A speculative but exciting research direction is to model CSI data as a form of "language"—i.e., treating it as a structured, symbolic representation of environmental data suitable for processing with Large Language Models (LLMs). While this would require a complete shift in the current approach to Wi-Fi sensing, it may unlock new methods for generalization and abstraction.

Addressing these challenges and directions is critical to foster practical deployments of ISAC systems. However, we believe that Wi-Fi sensing can only move us closer to a pervasive yet privacy-aware ambient intelligence in real environments by focusing on scalability, robustness, and interpretability.

6. Conclusion

The pervasive nature of Wi-Fi and the rich information contained within CSI have fueled extensive research in wireless sensing. However, works should be potentially reproducible to promote the practical adoption of the solutions. In this survey, we focused on potentially reproducible CSI-based sensing proposals, establishing criteria based on the information on the CSI extraction tool used, the availability of the datasets, and the code. We provided a guide for researchers and practitioners seeking to build upon existing work and make meaningful contributions to the field. Ultimately, fostering a culture of reproducibility through the adoption of best practices in data sharing and code release is crucial for accelerating the transition of CSI sensing from academic labs to real-world applications and driving further innovation.

CRediT authorship contribution statement

Idio Guarino: Writing – original draft, Visualization, Project administration, Methodology, Investigation, Conceptualization. **Damiano Carra:** Writing – review & editing, Writing – original draft, Project administration, Methodology, Conceptualization. **Marco Cominelli:** Writing – review & editing, Writing – original draft, Validation, Methodology. **Francesco Gringoli:** Writing – review & editing, Supervision, Conceptualization. **Renato Lo Cigno:** Writing – review & editing, Validation, Supervision, Conceptualization.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

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Data availability

No data was used for the research described in the article.

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