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SURVEY ARTICLE

Textile-Sensing Wearable Systems for Continuous Motion Angle Estimation: A Systematic Review

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ABSTRACT

Textile sensors have demonstrated significant potential in next-generation wearable systems due to their excellent performance and unobtrusive nature. By building specialized sensing networks and algorithms, textile-based wearable systems can estimate the continuous motion angles of human joints with desirable accuracies. This article offers a systematic review aimed at identifying key challenges in this field and encouraging further applications of textile strain sensor networks within the human–computer interaction (HCI) community. To achieve this, we conducted an exhaustive literature search across four major databases: IEEE Xplore, PubMed, Scopus, and Web of Science, spanning from January 2016 to August 2023. Applying inclusion and exclusion criteria, we narrowed down 2684 results to a total of 24 relevant papers. To analyze these studies, we proposed a framework that incorporates both technical aspects – such as textile strain sensors, sensor placement, algorithms, and technical evaluations – and contextual factors like target users, wearability, and application scenarios. Our analysis uncovered two critical research gaps: First, it exists an incongruity between the development of textile-based wearables and the advancements in textile sensors. Second, there is a noticeable absence of contextual design considerations in this specific domain. To address these issues, we offer discussions and recommendations from three perspectives: 1) enhancing the robustness of textile-sensing networks, 2) improving wearability, and 3) expanding application scenarios.

KEYWORDS
Textile sensing network; joint angle estimation; motion monitoring; wearable technology

1. Introduction

The rapid growth of wearable technologies has driven the development of wearable systems for human motion monitoring, which has gained increasing attention in the engineering and Human-Computer Interaction (HCI) fields (M. Chen et al., 2017; Liang et al., 2021; Skach et al., 2018). According to the taxonomy proposed by Lopez-Nava and Munoz-Melendez (2016), human motion monitoring with wearable sensors can be divided into two categories: movement measurement and movement classification. Different from the latter, movement measurement emphasizes quantifying motion data, with joint angles being a critical parameter to monitor. To take it a step further, the *continuous* joint angle monitoring, which means the joint angles can be predicted and outputted continuously with time-series sensing signals, has been considered a significant potential in specific scenarios, such as such as rehabilitation (Poitras et al., 2019) and athletics (Edwards et al., 2023; Van der Kruk & Reijne, 2018). Specifically, with continuous rehabilitation movement angles, it is possible to efficiently evaluate the extent to which patients are developing unexpected abnormal movements, thereby providing timely guidance and correction and accelerating the recovery program (Tan et al., 2023). Within the domain of sports science, the capability for continuous monitoring of motion angles offers valuable insights into athlete performance and may preempt injuries through early detection of incorrect postures or movements (Edwards et al., 2023; Van der Kruk & Reijne, 2018).

Among various sensing technologies for human joint angles monitoring, textile strain sensors have distinguished themselves as apt instruments for the task of estimating motion angles. By seamlessly incorporating conductive fibers, polymers, or other responsive materials into fabric structures (Islam et al., 2020), textile strain sensors are able to detect human motion as their electrical properties such as resistance or capacitance would change when the fabric is stretched according to human motion. Most importantly, thanks to their unique wearable features, they are widely regarded as one of the ideal marriages of functionality and wearability, heralding the next frontier in wearable technology (Islam et al., 2020; C. Jin & Bai, 2022; Q. Shi et al., 2019). One of their most compelling advantages is their superior wearability, which offers a human-centric approach to data collection that traditional sensors cannot rival. Specifically, their soft, breathable, and lightweight properties make them ideal for wearable applications, adding minimal weight while maximizing comfort. Furthermore, the

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dimensional compatibility (Hwang et al., 2022) allows textile sensors to be effortlessly and seamlessly integrated into clothing or other substrates, with a high degree of flexibility across various dimensions, such as fibers, yarns, and fabrics(Chen et al., 2024; J. Wang et al., 2020; Xiong et al., 2021). For example, when woven into garments, they naturally conform to the body's shape and movements, offering unparalleled comfort and freedom of motion, which is particularly vital for long-term, continuous monitoring applications. All these features enable textile sensors superior to conventional optical motion-capture systems, which often necessitate external setup, or inertial measurement units (IMUs) that compromise the wearability of the systems into which they are integrated (Caeiro-Rodríguez et al., 2021; Zhang et al., 2020).

Beyond aforementioned wearable features, the recent substantial progress from material science has created a unique opportunity for HCI community to broaden the applicability of textile-sensing wearable systems for the real-time monitoring of joint angles across a variegated spectrum of contexts and applications. These advancements not only involve the incorporation of state-of-the-art materials such as nanomaterials but also extend to the development of new functionalities, such as energy harvesting e-textiles (Bhattarai et al., 2023; Dong et al., 2022; M. Li et al., 2022; M. Li et al., 2023). Additionally, researchers have made strides in enhancing the practical attributes of these textile sensors, including their washability and durability (Nikolova et al., 2021; Shak Sadi & Kumpikaitė, 2022). As such, there are plenty of studies which can offer insights and available resources for HCI community to design and develop all-in-one wearable systems that are capable of monitoring continuous joint angles.

However, despite the clear benefits of wearable systems that utilize textile strain sensors for continuous motion angle estimation and concrete advancements from material science, there is a noticeable absence of systematic reviews that approach these technologies from a HCI perspective. Most of the existing literature reviews have originated from the field of material science and predominantly focus on the textile sensors themselves. These studies delve into aspects like novel materials, working principles, fabrication techniques, and performance metrics specific to human motion detection (Huang et al., 2022; X. Liu et al., 2022; Pyo et al., 2021; Seyedin et al., 2019; Shuvo et al., 2022; J. Wang et al., 2020; Yu et al., 2021). While these contributions offer invaluable updates on the state-of-the-art in textile sensors, they overlook the challenges that are of concern to the HCI community. For example, how to apply textile strain sensors in wearable systems for joint angles estimation, how to introduce this textile-sensing technology in wider contexts. These challenges involve several critical aspects such as the design and implementation of textile-sensing networks and the signal processing methodologies required for continuous angle estimation. As a result, these reviews cannot provide a comprehensive framework or directional insights for future research focusing on HCI. To fill this gap, our systematic review distinguishes itself by prioritizing the design, development, and implementation of textile-sensing wearable systems that are proficient in estimating continuous human joint angles. Our objective is to both elucidate the existing challenges and discuss opportunities in this evolving field.

To fulfill this objective, this systematic review first undertakes a comprehensive literature search and introduces a novel framework centered on the implementation of wearable systems within a HCI standpoint. This framework encompasses both technical and contextual dimensions. Utilizing this framework as a guide, we categorize, inventory, and analyze studies that meet our criteria – namely, textile-sensing wearable systems capable of estimating continuous motion angles. In the discussion section, we identify two significant research gaps and offer insights for future investigations in three key areas: 1) enhancing the robustness of textile-sensing networks, 2) improving wearability, and 3) expanding application scenarios for this motion-monitoring technology. We anticipate that this systematic review will serve as a valuable resource for both seasoned researchers and newcomers alike, aiding in the development of a comprehensive understanding of the field and fostering inspiration for state-of-the-art innovations.

2. Methodology

2.1. Literature search strategy

To identify relevant literature on wearable systems for continuous human joint angle estimation with textile-sensing networks, we conducted a comprehensive search across four databases: IEEExplore, PubMed, Scopus, and Web of Science. Initially, we fully searched the studies published between January 2016 and July 2022. During the peer-review process, we conducted a second round of literature search to update our findings with publications released between August 2022 and August 2023. Both rounds included journal articles and peer-reviewed conference papers that were written in English. The search strategy involved following keywords: ("joint" OR "motion" OR "motor" OR "movement" OR "pose" OR "posture" OR "gesture") AND ("monitor*" OR "sens*" OR "estimat*" OR "measur*" OR "detect*" OR "track*" OR "captur*") AND ("textile" OR "fabric" OR "e-textiles" OR "yarn" OR "fabric-based" OR "textile-based") AND ("wearable").

2.2. Identifying eligible studies

We followed the Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) guidelines (Page et al., 2021) to systematically select eligible papers in both rounds. First, we removed duplicates after implementing the comprehensive search strategy. Then, two reviewers (RZ and QW) independently screened the titles and abstracts of the remaining articles. Subsequently, the same two reviewers independently read the full text to assess whether the papers met the inclusion and exclusion criteria. In the case of differing opinions, the reviewers reached agreements with other authors through discussion. If one research team published

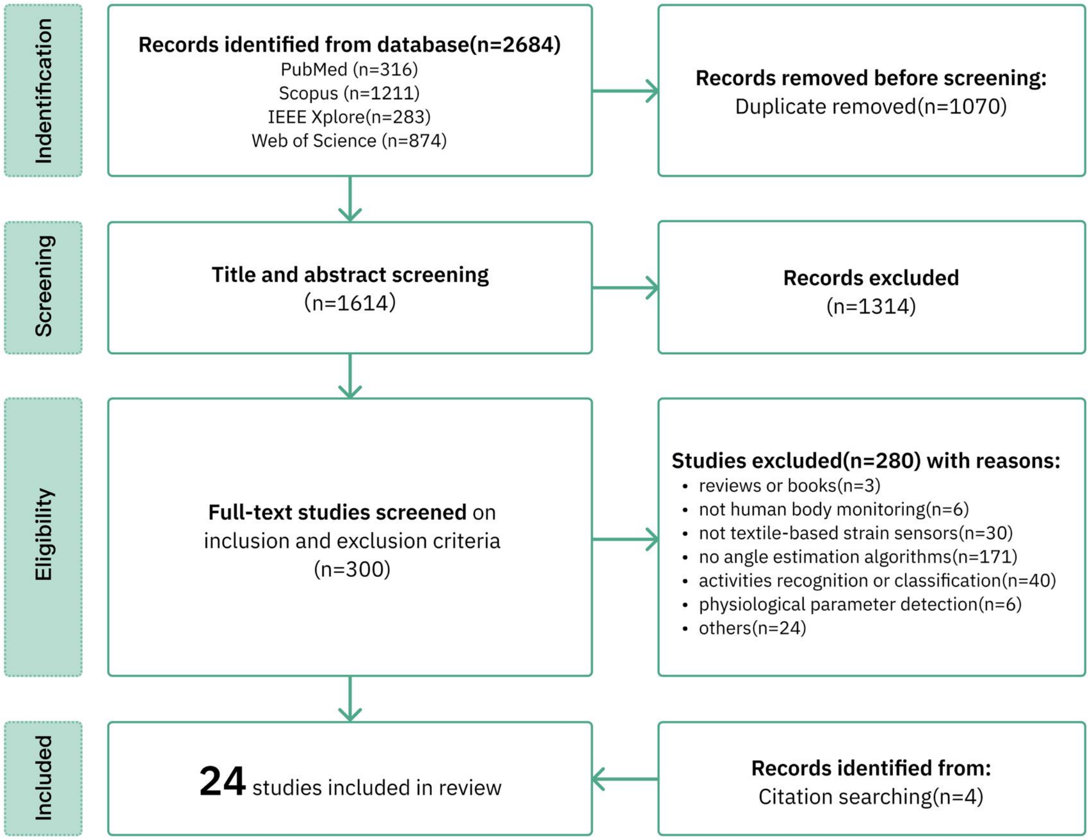

Figure 1. PRISMA flowchart of the results from literature research.

several articles related to the same wearable system, we included the most relevant one based on the inclusion criteria. The PRISMA flowchart illustrating the selection process is shown in Figure 1. The detailed inclusion and exclusion criteria are presented as follows.

2.2.1. Inclusion criteria

- The study concerned a wearable system equipping with a textile-sensing network.
- The textile-sensing network included rational data processing methods or algorithms that could predict continuous human joint angles from the time-series signals.
- The study reported monitoring performance, i.e., monitoring accuracy.
- The study was published between January 2016 and August 2023, and written in English.

2.2.2. Exclusion criteria

- Reviews or books.
- The systems were designed for robots rather than humans.
- The system was not based on textile strain sensors.
- The system was not capable of outputting continuous joint angles from textile sensing signals.

2.3. Data extraction with a new framework

After identifying eligible studies, we further classified and inventoried them with a novel framework. As shown in Figure 2, the framework considered both technical and contextual aspects, including crucial elements required for the development of a functional and usable wearable system with a textile-sensing network. The detailed instructions are provided below:

1. Technical matters: Once the specific joint to be monitored has been identified, the focus shifts to the construction of an effective textile-sensing network. Within the scope of this review, we deem three key aspects as critical for the development of such a network: i) *textile strain sensors*, which involves selecting the appropriate type of textile sensor as well as evaluating its sensing performance; ii) *sensor placement*, which concerns the strategic positioning of sensors around the target joint, especially in cases where multiple sensors are required to capture complex joint movements; and iii) *algorithms*, entailing the development of computational methods for real-time prediction of joint angles based on time-series data from the textile sensors. Upon the establishment of the network, a *technical evaluation* should be conducted to validate the system's reliability and accuracy in continuous human motion monitoring.
2. Contextual matters: In addition to the technical aspects, it is crucial to contemplate how this technology can be seamlessly integrated into clinical or real-world settings. One strategy involves embedding textile-sensing networks within wearable systems. This integration calls for further design considerations, such as *application*

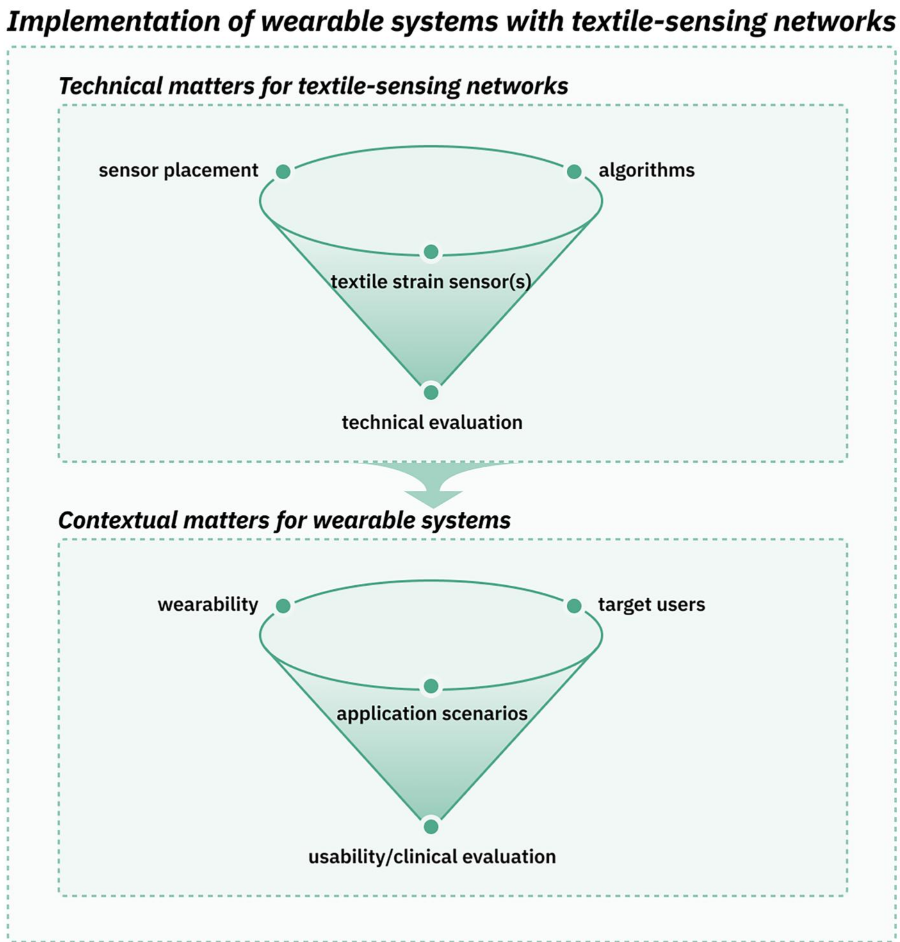

Figure 2. A framework centered on the implementation of wearable systems for joint angles estimation from a Human-Computer Interaction standpoint.

scenarios, which refer to the specific contexts where the technology will be deployed; *target user conditions*, which pertain to the unique characteristics or needs of users within those scenarios; and *wearability*, which assesses whether the wearable systems equipped with textile-sensing networks meet the wearability criteria for a given context. These multifaceted considerations necessitate *usability or clinical evaluations* to confirm the system's applicability for its intended use.

We applied this framework to analyze the eligible studies with both technical and contextual considerations. The findings were presented in the next section.

3. Findings

The literature search yielded a total of 2684 articles, with additional four articles included from citation searching. Following PRISMA guidelines, the full texts of 300 articles were retrieved. Ultimately, 24 papers that satisfied the predetermined inclusion criteria were selected for review and their key information was summarized in Table 1. To make it easier to track these articles in the following figures, we have numbered them from 1 to 24, which also can be found in Table 1.

3.1. Technical matters for textile-sensing networks development

Addressing particular technical challenges is essential for furthering the development of textile-sensing networks. However, prior to discussing these technical elements, the primary prerequisite is to identify the specific joint angles that need monitoring. Therefore, in this section, we first catalog the target joint angles covered in the studies that met our inclusion criteria. Subsequently, we present detailed findings on three critical aspects of textile-sensing network development: textile strain sensors, sensor placement, and algorithms. Lastly, we provide information regarding the technical evaluations conducted, with a special focus on the monitoring accuracy reported in these studies.

3.1.1. Target joint angles

The 24 included articles spanned a diverse range of joint angles, encompassing various anatomical regions as detailed in Figure 3. These studies examined joints such as the hip (Gholami et al., 2019; Tavassolian et al., 2020), knee (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Gholami et al., 2018; Gholami et al., 2019; Grassi et al., 2017; Gupta et al., 2021; S. Hu et al., 2019; Poomsalood et al., 2019; Ru et al., 2023; Totaro

Table 1. Summary chart of key information.

Number	References	Motion angles	Types	factor (GF)	Hysterisis	Linearity	Placement and numbers	Sensor placement strategies	Algorithms	Accuracy	Substrate	Method	Evaluation and participants number	Scenarios
1	Mokhlespour Esfahani et al.,(2017)	Trunk	Re	6	8%	Error = 2%	Back (N = 12)	Deformation measurement, and previous work	MLP	≪>2.7°	Tight shirt	–	TE (N = 3)	–
2	Totaro et al.,(2017)	Knee, ankle	Ca	–	–	–	Knee (N = 3) Ankle (N = 5)	Anatomy	Multiple linear regression	≪>4°	Knee brace Ankle brace	Adhesive	TE, UE (N = 2)	–
3	Grassi et al.,(2017)	Knee	Re	2.56	14.80%	0.998	Knee (N = 1)	Anatomy	Simple linear models	≪>8.9°	Knee brace	Fixed by hooks	TE (with a robot), UE (n = 1)	–
4	Esfahani & Nussbaum,(2018)	Shoulder, trunk	Re	6	8%	Error = 2%	Lower back (N = 5) Shoulder (N = 6)	Previous work	MLP	≪>1.3° (trunk) ≪>9.4° (shoulder)	Undershirt	–	TE (N = 16)	–
5	Maselli et al.,(2018)	Cervical	Re	2.56	14.80%	0.998	Neck (N = 2)	Anatomy	Simple linear models	≪>12.31° (fl) ≪>6.04° (lb) ≪>10.16° (ro)	(On Skin)	(On skin)	TE (N = 5)	–
6	Gholami et al.,(2018)	Knee	Re	–	–	–	Knee (N = 1)	–	Random forest + MLP	≪>6.97° (inter) ≪>3.02° (intra)	Tight trousers	Sewing	TE (N = 6)	–
7	R. Liu et al.,(2019)	Elbow	Re	~4.5	Quantified	Quantified	Elbow (N = 4)	Anatomy	Simple linear models	≪>9.69°	Sleeve	Adhesive and sewing	TE, UE (N = 10)	–
8	S. Hu et al.,(2019)	Knee	Re	–	–	–	Knee (N = 1)	–	Simple linear models	0.91r	(On Skin)	(On skin)	TE, UE (N = 1)	–
9	Rezaei et al.,(2019)	Trunk	Re	5	10%	Quantified	Back (N = 18)	Previous work	Random forest	≪>4.26° (fl) ≪>3.53° (lb) ≪>3.44° (ro)	Sleeveless shirt	Sewing	TE (N = 12)	–
10	Gholami et al.,(2019)	Hip, knee, ankle	Re	5	10%	Quantified	Pelvis (N = 4) Knee (N = 2) Ankle (N = 3)	Deformation measurement	CNN + MLP	≪>6.38° (inter) ≪>2.20° (intra)	Tight trousers	Sewing	TE (N = 10)	Sports (running)
11	Poomsalood et al.,(2019)	Knee	Ca	–	–	–	Knee (N = 3)	–	Multiple linear regression	≪>< 5° (7/9)	(On Skin)	(On skin)	TE (N = 9)	–
12	Y. Jin et al.,(2020)	Shoudler	Ca	1.23	1.50%	0.999	Shoulder (N = 8)	Anatomy, sensing test	Gradient boosting model based on decision trees	≪>4.5°	Tight shirt	Sewing	TE (N = 1)	–
13	Vu et al.,(2020)	Lumbar	Ca	–	–	–	Around the lumbar (N = 10)	Previous study	PCA + multiple linear regression	≪>9° (fl,lb) ≪>13.7° (ro)	(On Skin)	(On skin)	TE (N = 12)	Astronauts (spacesuit)
14	Tavassolian et al.,(2020)	Hip	In	0.055	–	0.985	Around the Pelvis (N = 4)	Deformation measurement	Random forest	≪>1.63° (sa) ≪>1.08° (fr) ≪>< 1.15° (tr)	Sport Shorts	Sewing	TE (N = 12)	Sports (running)
15	Lau & Soh,(2020)	Elbow	Re	–	–	–	Elbow (N = 1)	Anatomy and kinematics of the RPR Chain	Binary linear models	8.01≪>°–10.72≪>°	–	–	TE on testbed	–
16	Watson et al.,(2020)	Knee	Re	–	–	–	Knee (N = 1)	–	Binary linear models	≪>3.6° (average)	Knee brace	Adhesive & Sewing	TE (N = 6)	Rehabilitation
17	Zhu et al.,(2021)	Elbow	Re	–	–	–	Elbow (N = 6)	–	MLP with customised loss function	≪>8.78°	Elbowpad	Sewing	TE (N = 10)	–
18	Di Tocco, Carnevale, Bravi, et al. (2021); Di Tocco, Carnevale, Presti, et al. (2021)	Knee	Re	0.28	26.64%	Error = 23.9%	Knee (N = 1)	Deformation measurement	Binary linear models	≪>18.82°	Knee guard	Fixed by Metal Snaps	TE (N = 5)	Rehabilitation
19	Di Tocco, Carnevale, Bravi, et al. (2021); Di Tocco, Carnevale, Presti, et al. (2021)	Elbow	Re	–	–	–	Elbow (N = 1)	–	Binary linear models	≪>7.5°	Elbow guard	Fixed by buttons	TE (N = 2)	–
20	Gupta et al.,(2021)	Knee	Re	–	–	–	Knee (N = 1)	Anatomy Sensing test	Simple linear models	≪>16.46° (fl)	Knee brace	Adhesive & Sewing	TE (n = 6)	Rehabilitation
21	Robinson et al.,(2022)	Shoulder, Elbow	Re	–	–	–	Elbow (N = 1) Shoulder (N = 4)	Anatomy	CNN + MLP	≪>9.7° (elbow) ≪>2.6° (shoulder)	Tight shirt	–	TE	Robotics
22	Ru et al.,(2023)	Knee, elbow	Re	–	–	0.9835 ~ 0.9907	Knee (N = 1) Elbow (N = 1)	–	MLP	≪>2.68° (knee) ≪>3.04° (elbow)	Knee and elbow pads	–	TE (n = 1)	–
23	Zou et al.,(2023)	Knee	Re	–	–	–	Knee (N = 3)	Anatomy	Simple linear models	≪>< 6.15° (fl)	Knee brace	–	TE (with a prosthetic limb)	Rehabilitation Robotics
24	X. Chen et al.,(2022)	Elbow	Ca	–	–	0.999	Elbow (N = 6)	Sensing performance	LSTM + MLP	≪>9.82° (single user) ≪>10.98° (multiple motion types) ≪>11.81° (multiple users)	Elbow pad	Adhesive & hot pressed	TE (n = 12) UE (n = 9)	Rehabilitation Athletes

footnote:
1. Column Sensor Types: Re: Resistive textile sensors, Ca: Capacitive textile sensors, In: Inductive texitle sensors.
2. Column Algorithms: MLP: multilayer perceptron; CNN: convolution neural network; PCA: Principal component analysis.
3. Column Accuracy: fl: flexion/extension, lb: lateral bending, ro: rotation, sa: sagittal plane, fr: frontal plane, tr: transverse plane.
4. Column Evaluation and Participants number: TE: technical evaluation; UE: usability evaluation.
5. "-" means "Not mentioned."

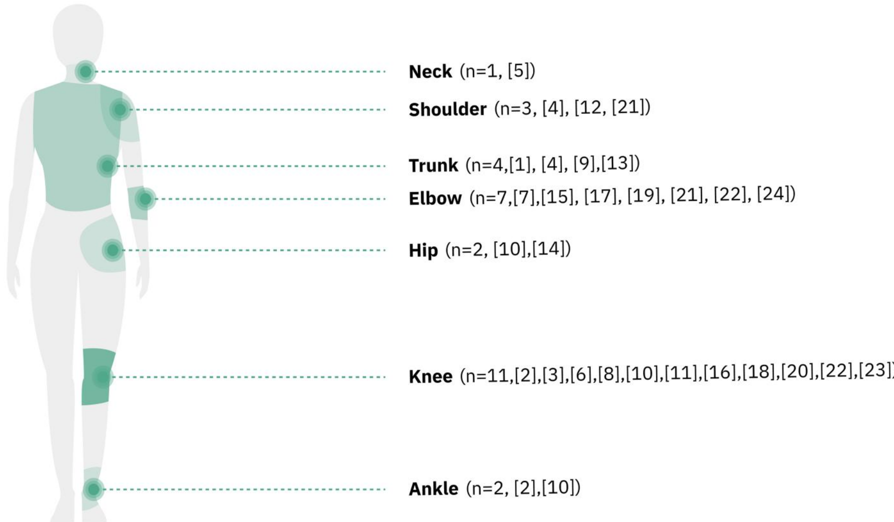

Figure 3. The illustration of monitored joints among 24 eligible studies.

et al., 2017; Watson et al., 2020; Zou et al., 2023), ankle (Gholami et al., 2019; Totaro et al., 2017), neck (Maselli et al., 2018), shoulder (Esfahani & Nussbaum, 2018; Y. Jin et al., 2020; Robinson et al., 2022), elbow(X. Chen et al., 2022; Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Lau & Soh, 2020; R. Liu et al., 2019; Robinson et al., 2022; Ru et al., 2023; Zhu et al., 2021), and trunk (Esfahani & Nussbaum, 2018; Mokhlespour Esfahani et al., 2017; Rezaei et al., 2019; Vu et al., 2020).

A significant focus was placed on lower body kinetics, with 11 of the 24 studies honing in on this area (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Gholami et al., 2018, 2019; Gupta et al., 2021; S. Hu et al., 2019; Poomsalood et al., 2019; Ru et al., 2023; Tavassolian et al., 2020; Totaro et al., 2017; Watson et al., 2020; Zou et al., 2023). Of these, eight dedicated their research to estimating knee joint angles in the sagittal plane (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Gholami et al., 2018, 2019; Gupta et al., 2021; S. Hu et al., 2019; Poomsalood et al., 2019; Ru et al., 2023; Totaro et al., 2017; Watson et al., 2020; Zou et al., 2023). It should be noted that three of these studies aimed for multi-joint monitoring; for example, in the study by Totaro et al. (2017), a brace with five textile strain sensors was developed to measure knee joint angles, as well as ankle joint angles in three planes (sagittal, front, and transverse plane). The smart legging proposed by Gholami et al. (2019) was configured to monitor hip, knee, and ankle joint angles concurrently, while the system proposed by X. Chen et al. (2022) was engineered to estimate both elbow and knee angles.

On the other hand, 12 studies centered on upper body joint angles (X. Chen et al., 2022; Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Esfahani & Nussbaum, 2018; Y. Jin et al., 2020; R. Liu et al., 2019; Maselli et al., 2018; Mokhlespour Esfahani et al., 2017; Rezaei et al., 2019; Robinson et al., 2022; Ru et al., 2023; Vu et al., 2020; Zhu et al., 2021). The elbows were often the focus, examined in a singular plane(X. Chen et al., 2022; Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; R. Liu et al., 2019; Robinson et al., 2022; Ru et al., 2023; Zhu et al., 2021), as were complex multi-plane neck angles (Maselli et al., 2018) and intricate shoulder movements (Esfahani & Nussbaum, 2018; Y. Jin et al., 2020; Robinson et al., 2022). Additionally, four articles delved into three-degree-of-freedom monitoring of the trunk or lumbar region (Esfahani & Nussbaum, 2018; Mokhlespour Esfahani et al., 2017; Rezaei et al., 2019; Vu et al., 2020), which involved observing flexion, lateral bending, and rotational angles.

Worth noting is that X. Chen et al. (2022); Grassi et al. (2017); Lau and Soh (2020) offered more general solutions, applicable to various body parts. The systems in these studies are capable to measure flexion and extension in human movements, such as those involving the knee and elbow, rather than focusing on a single specific joint.

Methodologies for defining the monitored angles varied among the studies. Simple anatomical models were often used for joints with a single degree of freedom, like the knee, elbow, and neck. In several instances, knee and elbow joints were considered pulley systems (X. Chen et al., 2022; Grassi et al., 2017; Gupta et al., 2021; S. Hu et al., 2019; Lau & Soh, 2020; Robinson et al., 2022; Ru et al., 2023; Watson et al., 2020; Zou et al., 2023). The neck joint in study by Maselli et al. (2018), for instance, was treated as a spherical joint allowing for various types of movement. Alternatively, nine studies opted for vector-based or geometric relationships using reflective markers affixed to anatomical positions (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Gholami et al., 2018, 2019; Poomsalood et al., 2019; Rezaei et al., 2019; Tavassolian et al., 2020; Totaro et al., 2017; Zhu et al., 2021). Some, like Y. Jin et al. (2020), Mokhlespour Esfahani et al. (2017), and Vu et al. (2020), adhered to coordinate systems recommended by the International Society of Biomechanics (ISB)(Wu et al., 2002, 2005) for complex motions. However, the study by Esfahani and Nussbaum (2018) lacked explicit definitions or references for the monitoring of multi-degree-of-freedom shoulder and low-back movements.

3.1.2. Textile strain sensors

The selection of textile sensors was the first consideration among the three matters of developing a textile-sensing network. In the context of continuous joint angle monitoring, textile strain sensors were applied in all included cases. The general working principle of textile strain sensors is that the sensing parameters would change while stretching caused by skin deformation or joint movement, thus the sensors are often designed as long stripes to accommodate the direction of stretching.

Although the fundamental working principle mentioned above applies to all strain sensors, the characteristics and performance of different sensors vary much according to different sensing principles (J. Wang et al., 2020), such as resistive effect, capacitive effect, etc. Among the 24 eligible studies, 3 different sensing principles were found, which brought three types of textile strain sensors:

- Resistive textile strain sensor, $n = 18$ (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Esfahani & Nussbaum, 2018; Gholami et al., 2018, 2019; Grassi et al., 2017; Gupta et al., 2021; S. Hu et al., 2019; Lau & Soh, 2020; R. Liu et al., 2019; Maselli et al., 2018; Mokhlespour Esfahani et al., 2017; Rezaei et al., 2019; Robinson et al., 2022; Ru et al., 2023; Watson et al., 2020; Zhu et al., 2021; Zou et al., 2023).
- Capacitive textile strain sensor, $n = 5$ (X. Chen et al., 2022; Y. Jin et al., 2020; Poomsalood et al., 2019; Totaro et al., 2017; Vu et al., 2020).
- Inductive textile strain sensor, $n = 1$ (Tavassolian et al., 2020).

To further analysis, the different performance among these sensors, three key parameters that were always used for describing sensors' performance (Homayounfar & Andrew, 2020; Nesser & Lubineau, 2021), namely sensitivity, hysteresis, and linearity, were paid attention in this review as follows:

- Sensitivity indicates the accuracy and efficiency of the sensor and is usually evaluated by gauge factor (GF), which is given by GF = $\ll>\triangle R/R_0\varepsilon$, where $\ll>\triangle R$ denotes the resistance variation (i.e., the difference between R as the resistance value under deformation and R_0 as the initial value), and ε is the applied strain (Homayounfar & Andrew, 2020). Usually, the higher GF denotes higher sensitivity.
- Hysteresis reflects that there is no unique correspondence between the observed sensing signal readings and stretching length (Schmool & Markó, 2018). Typically, different sensing signal value curves will be presented under loading and unloading, while higher hysteresis means larger differences between two curves.
- Linearity, which always indicates the linear working range of textile strain sensor, measures the stability of the signal over an application range and is determined by the percentage of deviation of the output signal from the linear regression line (Homayounfar & Andrew, 2020), and higher linearity implies a more predictable relation between strain and readings.

Resistive textile strain sensors are the most widely used sensors for measuring human movement. Most of them exhibit excellence in sensitivity (Homayounfar & Andrew, 2020; X. Wang et al., 2022), and are worth considering for studies demand high sensitivity and large strain range along with large deformation. Among three types of sensors, resistive textile strain sensors were widely used in 18 of the eligible studies, measuring both one-degree-of-freedom and multi-degree-of-freedom joint angles, including trunk (Esfahani & Nussbaum, 2018; Mokhlespour Esfahani et al., 2017; Rezaei et al., 2019) hip (Gholami et al., 2019), knee (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Gholami et al., 2018, 2019; Grassi et al., 2017; Gupta et al., 2021; S. Hu et al., 2019; Robinson et al., 2022; Ru et al., 2023; Watson et al., 2020; Zou et al., 2023), ankle (Gholami et al., 2019), shoulder (Esfahani & Nussbaum, 2018; Robinson et al., 2022), neck (Maselli et al., 2018), and elbow (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Lau & Soh, 2020; R. Liu et al., 2019; Robinson et al., 2022; Ru et al., 2023; Zhu et al., 2021). These sensors work on the resistive effect (J. Wang et al., 2020), where an external force deforms the strain sensors and changes the resistance of the conductive textile, thus measuring human motion by sensing signals variation. While this principle provides textile strain sensors with high sensitivity compared to capacitive ones, it also leads to considerable hysteresis (X. Wang et al., 2022). For instance, among the 15 studies with resistive strain sensors, eight of them reported GF values, with seven of them ranging from 2.56 to 6 (Esfahani & Nussbaum, 2018; Gholami et al., 2019; Grassi et al., 2017; R. Liu et al., 2019; Maselli et al., 2018; Mokhlespour Esfahani et al., 2017; Rezaei et al., 2019), and except one study by Di Tocco, Carnevale, Bravi, et al. (2021); Di Tocco, Carnevale, Presti, et al. (2021) with relatively low GF of 0.28. However, the hysteresis tended to be obvious in these studies, ranging from 8% to 14.8% (Esfahani & Nussbaum, 2018; Gholami et al., 2019; Grassi et al., 2017; Maselli et al., 2018; Mokhlespour Esfahani et al., 2017; Rezaei et al., 2019), and even the hysteresis in study by Di Tocco, Carnevale, Bravi, et al. (2021); Di Tocco, Carnevale, Presti, et al. (2021) reached 26.64%. Notably, in the work from R. Liu et al. (2019), to avoid the deviation caused by hysteresis, textile pressure sensors were employed to assist in the determination of the elbow motion state. In terms of linearity, most of the studies reported excellent performance although only five studies reported it quantitatively (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Esfahani & Nussbaum, 2018; Grassi et al., 2017; Maselli et al., 2018; Mokhlespour Esfahani et al., 2017), with the highest correlation coefficient being ≪>$R^2 = 0.998$ (Grassi et al., 2017; Maselli et al., 2018).

As for capacitive strain sensors, they generally have relatively low sensitivity, while they offer high linearity and negligible hysteresis (S. Kim et al., 2017). Therefore, capacitive sensors are preferable considered for scenarios requiring high stability. Among 24 studies, five employed capacitive textile strain sensors to monitor knee (Poomsalood et al., 2019; Totaro et al., 2017), ankle (Totaro et al., 2017), shoulder(Y. Jin et al., 2020), trunk (Vu et al., 2020), or elbow (X. Chen et al., 2022). These sensors operate similarly to conventional capacitors, using a three-layer sandwich structure (J. Wang et al., 2020). Specifically, they use conductive fabrics as electrodes and elastic insulating materials as the medium. When an external force is applied, it causes a change in capacitance due to the distance or parallel area of the capacitor plates, the distance between the two textile electrodes, and the relative permittivity of the capacitive medium changes. Consequently, joint angles could be monitored by tracking capacitance variation. In general, capacitive sensors achieve lower hysteresis than resistive strain sensors (X. Wang et al., 2022). For example, the hysteresis reported in study by Y. Jin et al. (2020) was only 1.5%, which was the lowest among the included studies. And capacitive sensors are also reckoned to excel at linearity (Homayounfar & Andrew, 2020). The two studies(Y. Jin et al., 2020; Zou et al., 2023) reporting linearity among five studies both achieved a superior correlation coefficient of ≪>$R^2 = 0.999$. However, compared with resistive sensors, capacitive strain sensors generally tend to show lower sensitivity (X. Wang et al., 2022). The study by Y. Jin et al. (2020) reported their GF of 1.23, which was significantly lower than most resistive sensors among the eligible studies.

Inductive textile strain sensors were used in only one study that aimed at hip joint angle monitoring (Tavassolian et al., 2020). While these sensors have low sensitivity, with a GF of only 0.055, which is far from the other types of sensor. They operate on the principles of electromagnetic induction, and involve copper wire coiled around an elastic thread. The resulting copper-coiled elastic thread was integrated into sports shorts to monitor hip angles. External forces cause variations in the inductance and self-inductance coefficients, which in turn leads to changes in voltage and current output. These changes enable the determination of joint angles. But note that this type of sensor exhibits remarkable performance in terms of relaxation, as it shows no relaxation during the experiment, which might be beneficial for ultra-long-term use.

3.1.3. Sensor placement

Designing a textile-sensing network for continuous joint angle monitoring necessitates careful consideration of the number, location, and orientation of textile sensors. These variables significantly influence the effectiveness of the textile-sensing network (Mattmann et al., 2007; Mokhlespour Esfahani et al., 2017). To systematically catalog and illustrate the sensor placement formulas employed across 24 studies, we present a unified schematic in Figure 4. This schematic encompasses the number, location, and approximate orientation of the textile sensors, as well as the strategies guiding their placement.

The number of textile strain sensors deployed in such networks is contingent upon the complexity of the movement being monitored. Generally, movements with higher degrees of freedom require a greater number of sensors for accurate measurement. For instance, monitoring a three-degree-of-freedom ankle joint is more complicated than monitoring a single-degree-of-freedom knee joint, thus necessitating additional sensors. Of the eligible studies, ten utilized a single textile strain sensor for estimating flexion and extension angles around the knee or elbow joint (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Gholami et al., 2018; Grassi et al., 2017; Gupta et al., 2021; S. Hu et al., 2019; Lau & Soh, 2020; Robinson et al., 2022; Ru et al., 2023; Watson et al., 2020). Notably, although three textile sensors were integrated into the knee brace in the study by Gupta et al. (2021), only one sensor's data was utilized for angle estimation. Conversely, 11 other studies employed between 2 and 9 textile strain sensors for single-planar and multi-planar joint angle estimations (X. Chen et al., 2022; Gholami et al., 2019; Y. Jin et al., 2020; R. Liu et al., 2019; Maselli et al., 2018; Poomsalood et al., 2019; Robinson et al., 2022; Tavassolian et al., 2020; Totaro et al., 2017; Zhu et al., 2021; Zou et al., 2023). A notable case among them, is the elbow pad proposed by X. Chen et al. (2022) that equipped with six sensors for algorithm and wearability concerns. In the studies aimed at monitoring trunk angles (Esfahani & Nussbaum, 2018; Mokhlespour Esfahani et al., 2017; Rezaei et al., 2019; Vu et al., 2020), 12, 11, 18, and 10 textile strain sensors were allocated respectively to monitor the trunk angles with flexion, lateral bending, and rotation.

Regarding sensor location and orientation, various strategies have been adopted. The overarching objective is to position the textile sensors in areas experiencing maximum skin deformation during movement. This ensures that the sensors operate within their effective working ranges. Among the 24 studies, seven studies did not specify their methods (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Gholami et al., 2018; S. Hu et al., 2019; Poomsalood et al., 2019; Ru et al., 2023; Watson et al., 2020; Zhu et al., 2021), which indicated that they decided the sensor placement by empirical anatomy knowledge. These studies generally focused on simple, single-degree-of-freedom joints like the elbow and knee. In such cases, relying on empirical anatomical knowledge to identify maximum deformation areas was deemed acceptable.

While, the other 14 studies clearly explained the sensor placement strategies, including four categories as shown as follows:

- Anatomy analysis (X. Chen et al., 2022; Grassi et al., 2017; Gupta et al., 2021; Y. Jin et al., 2020; Lau & Soh, 2020; R. Liu et al., 2019; Maselli et al., 2018; Robinson et al., 2022; Totaro et al., 2017; Zou et al., 2023).

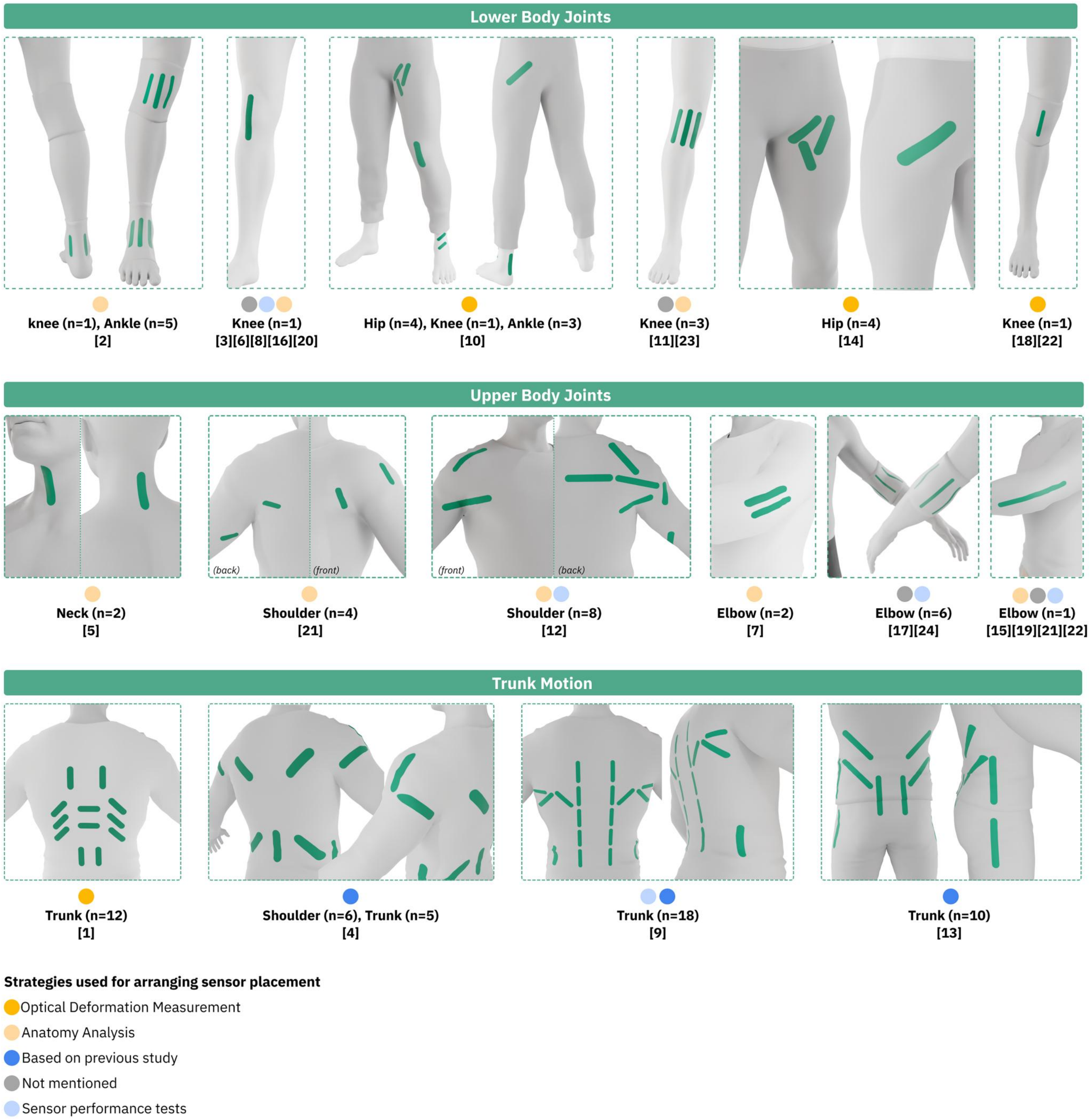

Figure 4. The schematic textile strain sensor placement strategies of the 24 eligible studies.

- Optical deformation measurements (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Gholami et al., 2019; Mokhlespour Esfahani et al., 2017; Tavassolian et al., 2020).
- Based on previous studies that measured deformation (Esfahani & Nussbaum, 2018; Rezaei et al., 2019; Vu et al., 2020).
- Sensor performance tests (X. Chen et al., 2022; Gupta et al., 2021; Y. Jin et al., 2020; Lau & Soh, 2020; Rezaei et al., 2019).

Locating textile strain sensors based on anatomical analysis is a straightforward approach. For example, the authors in one study elucidated maximum deformation areas around the knee joint by leveraging anatomical knowledge (Totaro et al., 2017). Others determined sensor locations through the analysis of anatomical models' rotational axes (R. Liu et al., 2019; Maselli et al., 2018). In the study by Y. Jin et al. (2020), capacitive textile strain sensors were placed vertically along non-extension lines according to anatomy first, and capacitance changes tests were performed by iteration of sensor locations and orientations to optimize the sensor placement.

Deformation measurement is considered the most reliable strategy compared to others (Mokhlespour Esfahani et al., 2017), because it provides quantified evidence to determine the sensor placement. For example, the sensors' deformation study on the upper trunk by Mattmann et al. (2008) was referenced by Esfahani and Nussbaum (2018) and Rezaei et al. (2019). This method was usually applied in the textile-sensing networks that aimed at monitoring multi-degree-of-freedom human motion, gaining higher data collection accuracy, or using fewer sensors. In the studies by Di Tocco, Carnevale, Bravi, et al. (2021); Di Tocco, Carnevale, Presti, et al. (2021); Gholami et al. (2019); Mokhlespour Esfahani et al. (2017), it was exhaustively described how this method was carried out: typically, the fabric deformation was measured by inviting subjects to wear tight-fitting garments with reflective markers and perform preset actions in the optical motion capture lab environment, and the set of marker points with largest deformation would be selected as the references for sensors' location. Based on this strategy, deformation was measured around the pelvis (Gholami et al., 2019; Tavassolian et al., 2020), the knee joint (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021), and the upper trunk (Mokhlespour Esfahani et al., 2017). Although the study by Mokhlespour Esfahani et al. (2017) did not use a continuous motion tracking system, sensor placement was determined by taking photos of the 32 movements made by one subject wearing a tight garment with 90 reflective markers. The larger deformation area was selected for sensor placement through qualitative analysis of these photos. Vu et al. (2020) located the sensors by drawing on the layout experience from Mokhlespour Esfahani et al. (2017) due to its higher credibility.

3.1.4. Algorithms

With the guidance from the proposed framework, the third technical matter concerns with the construction of algorithms capable of estimating continuous joint angles with time-series textile sensing data. To accomplish this, raw textile sensing data undergo at least three distinct stages of processing in a conventional data pipeline. First, raw textile data are collected and pre-processed into a format suitable for the algorithm. Typically, raw data from textile sensors are usually in an arbitrary range and also a serial form, and the conventional operation will be to normalize the sensor readings range and save them in matrices. Then, the formatted data, like a matrix, will be transferred to a feature extraction algorithm, which can extract relevant features for the target task. When dealing with a single textile sensor, researchers usually extract features from the temporal pattern change. Finally, these features will be fed into an inference model that can produce the final results of target task. For angle estimation, the inference model can identify the specific patterns extracted by the feature extractor and assess their relevance to the moving angles. Based on this assessment, the model can estimate the moving angle accordingly.

Within this pipeline, two key elements have a significant impact on algorithm performance and are worth considering: 1) data fusion between each step of multiple textile sensors (if applicable) that refers to the method of combination for data from textile sensors in textile-sensing networks, and 2) the inference models that indicates the mathematical model preset to infer the angle from the processed sensor data.

In general, according to different stages to apply fusion operations, data fusion of multiple sensors can be performed at three distinct levels: data-level, feature-level, and decision-level (Gravina et al., 2017; Qiu et al., 2022). Among the eligible studies, eight studies employed only a single sensor, and also seldom studies in the rest employed data fusion techniques, with only five studies at data-level fusion (Gholami et al., 2018, 2019; Ru et al., 2023; Tavassolian et al., 2020; Vu et al., 2020), one study at feature-level (Gholami et al., 2019), and one study at decision level (Totaro et al., 2017).

In data-level, fusion operations integrate data from multiple sensors into a single data set before feature extraction, mainly including denoising, feature pre-extraction, data classification, and data compression. Some eligible studies applied data-level fusion techniques to enhance the performance of their models. For example, Vu et al. (2020) used principal component analysis (PCA) to reduce the data from ten sensors to five principal dimensions, and then built a regression model based on the reduced data to estimate lumbar angles. Ru et al. (2023) integrated five one-dimensional sensor signal series into a two-dimensional matrix. This matrix was subsequently processed by a 2D convolutional neural network (CNN), facilitating the exploration of inter-series relationships. Tavassolian et al. (2020) performed arithmetic operations on each pair of sensor signal values, such as addition, subtraction, division, and multiplication, and reported better results on hip angles monitoring than using the original values. Gholami et al. (2019) calculated the first and second derivatives of the raw signal from nine textile sensors, and used them along with the raw signal to train their model. Unlike the other studies that fused data from multiple sensors or sources, Gholami et al. (2018) aimed at knee joint angles and applied a broader sense of data-level fusion by extracting features from one sensor signal in different time segments, resulting in 788 features that were fed to their model. These studies demonstrated that such data-level fusion in time dimension improved their model compared to using the raw signal alone.

At feature-level, fusion operations combine features extracted from multiple data sources before sending them to an inference model. Gholami et al. (2019) fused features extracted by CNN to achieve their goal. They firstly employed data-level fusion before feature-level fusion as aforementioned. Specifically, they first combined and pre-processed data from nine sensors and formed them as a matrix of shape (60×27), which then was fed into four layers of 2D CNN, eventually extracting 100 features of shape (26×27). These features were subsequently flattened into one dimension and sent into a multilayer perceptron (MLP) for angle estimation of hip, knee, and ankle.

At decision-level, fusion operations synthesize the results produced by the inference model on individual sensors to make a further decision. R. Liu et al. (2019) integrated a pressure sensor into their textile, which can detect the pressure generated by joint movement. This enables their textile to differentiate two motion states (loading, unloading) and a motionless state, consequently deciding the model used for final angle estimation.

Besides data-fusion, inference model employed also matters. Based on their methods of inference, these systems can be generally divided into two categories: deduction and induction. Specifically, deductive approaches involve leveraging known knowledge, such as geometry, to build a model for predicting joint angles based on sensing data. Inductive approaches, on the other hand, indicate adapting models to data collected from sensors without making any assumptions on human's movement. In another word, models need to discover the hidden relationship between sensor data and human's movement by themselves.

Among the eligible studies, deductive methods mainly relied on geometry principles and deformation of sensors, such as elongation or strain, to estimate joint angles (Grassi et al., 2017; Gupta et al., 2021; S. Hu et al., 2019; R. Liu et al., 2019; Maselli et al., 2018) which was related to raw sensor characteristics such as capacitance or resistance values. For example, S. Hu et al. (2019) assumed that the resistance change of the sensor was proportional to its change in length, and thus the change in the knee joint angle could be determined by multiplying the resistance change by the sensor sensitivity and dividing it by the radius of the knee joint. Additionally, Maselli et al. (2018) calculated the joint angle by dividing the elongation of each pair of sensors by the radius of the neck joint. In another study, R. Liu et al. (2019) first analyzed the anatomy of elbow joints to identify the geometric relationship between the deformation and the rotation of joint bones. They found that the joint rotation angle was linearly related to the difference between stretch lengths sensed by the dual strain fabric sensors.

In comparison, inductive methods have been used in a more diverse range of studies (X. Chen et al., 2022; Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Esfahani & Nussbaum, 2018; Gholami et al., 2018, 2019; Y. Jin et al., 2020; Lau & Soh, 2020; Mokhlespour Esfahani et al., 2017; Poomsalood et al., 2019; Rezaei et al., 2019; Robinson et al., 2022; Ru et al., 2023; Tavassolian et al., 2020; Totaro et al., 2017; Vu et al., 2020; Watson et al., 2020; Zhu et al., 2021; Zou et al., 2023). These methods can be further categorized into two classes: simple linear regression and advanced machine learning.

Eight studies (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Lau & Soh, 2020; Poomsalood et al., 2019; Totaro et al., 2017; Vu et al., 2020; Watson et al., 2020; Zou et al., 2023) utilized simple linear regression to fit data pairs of sensor data and ground-truth joint angles, among which, the similar calculation patterns were shown. Take the study by Poomsalood et al. (2019) as an example, linear algebra techniques were used to determine the equation coefficient between sensor output signals and quaternions obtained from an OptiTrack system.

Eleven studies (X. Chen et al., 2022; Esfahani & Nussbaum, 2018; Gholami et al., 2018, 2019; Gupta et al., 2021; Y. Jin et al., 2020; Mokhlespour Esfahani et al., 2017; Rezaei et al., 2019; Robinson et al., 2022; Ru et al., 2023; Tavassolian et al., 2020; Zhu et al., 2021) introduced advanced machine learning algorithms into their work, including random forest and neural networks (NNs). For instance, Esfahani and Nussbaum (2018) used a MLP with one hidden layer containing 60 or 200 neurons to explore the relationship between raw sensor signals and angles of the low-back and shoulder. In another study (Rezaei et al., 2019), random forest was used to achieve the same mission for the trunk. Gholami et al. (2018) combined these two approaches into their model by using random forest to select important time-serial features, which were then fed into an MLP containing three hidden layers with ten neurons each. Popular NN like CNN and recurrent NN (RNN) are also used in several studies (X. Chen et al., 2022; Gholami et al., 2019; Robinson et al., 2022). Gholami et al. (2019) used four layers of CNN to extract time-serial features, which were then fed into an MLP containing one hidden layer with 100 neurons. Zou et al. (2023) used six layers of long short-term memory (LTSM) for feature extraction of six sensors, followed by one full connection layer for converting the output of LSTM to readable angle. It worth to mentioning that, within the inductive methods, advanced machine learning methods appeared to outperform simple regressions regarding absolute errors, which was evidenced by comparison results in studies by Esfahani and Nussbaum (2018); Totaro et al. (2017) that conducted both types of methods on their data.

Furthermore, it is important to underscore that two studies (X. Chen et al., 2022; Zhu et al., 2021) tackled the issue of signal variation due to sensor aging or dislocation by employing transfer learning techniques. Specifically, Zhu et al. (2021) achieved sensor compatibility across different aging stages with a unique algorithm. They introduced a specialized loss function designed to minimize the maximum mean discrepancy (MMD) between prediction outcomes generated by new and aged sensors. On the other hand, utilizing unsupervised transfer learning, X. Chen et al. (2022) demonstrated system robustness in the face of arbitrary circuitry modifications and certain lateral displacements of their sensing sleeve. Moreover, their approach yielded satisfactory performance across diverse users, joints, and motions, employing a unified model. They achieved this mainly depending on two steps. Initially, they applied fuzzy entropy calculations to the sensor data, followed by a reordering of the input data sequence. This step ensured that the order of the data was not contingent upon their inherent spatial positions but was instead related to their positional relevance to human joints. Subsequently, they computed the MMD between outcomes derived from the original dataset and those stemming from new data to serve as the loss function in their transfer learning framework.

In addition to the types of algorithm models, the subjects who use the models also matter. Several studies, such as the ones by Esfahani and Nussbaum (2018); Gholami et al. (2018, 2019), have conducted both intra-subject and inter-subject tests on their models. Intra-subject testing refers to training and testing the model on the same individuals or group, while inter-subject testing refers to training the model on one group and testing it on another group. The angle monitoring errors in the studies by Esfahani and Nussbaum (2018); Gholami et al. (2018, 2019) demonstrated that intra-subject testing consistently outperforms inter-subject testing, which indicated that individual discrepancy plays a non-negligible role in joint angle estimation by wearable.

3.1.5. Technical evaluation

Technical evaluation is a crucial step in verifying the efficiency and reliability of the proposed textile-sensing networks. Figure 5 displays the indicators used to evaluate the textile-sensing networks among the included studies, including accuracy test in labs (all studies), repeatability (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Maselli et al., 2018; Tavassolian et al., 2020), accuracy test in daily life scenarios (S. Hu et al., 2019; Totaro et al., 2017), robustness (R. Liu et al., 2019; Mokhlespour Esfahani et al., 2017; Totaro et al., 2017), and washability (X. Chen et al., 2022; R. Liu et al., 2019; Watson et al., 2020).

All studies conducted accuracy evaluation in a laboratory environment, typically involving participants donning prototypes equipped with textile-sensing networks and performing target movements in a laboratory setting. The monitoring accuracy of the suggested textile-sensing networks was evaluated by comparing the angle monitoring data from the proposed system with ground-truth angles. Besides, two studies also made the evaluation in daily life scenarios (S. Hu et al., 2019; Totaro et al., 2017). Of the 24 studies examined, only R. Liu et al. (2019), Grassi et al. (2017) and X. Chen et al. (2022) evaluated users' subjective perceptions, focusing on the wearable experience, i.e., comfort, of the wearable systems. As shown in Figure 5, the comfort was the only one indicator found used for evaluating the usability among the eligible studies.

Considering that washability presents a recurrent challenge in real-world applications, it is important to note divergent findings across studies. For example, X. Chen et al. (2022) assert that their sensors can withstand machine washing for more than 60 cycles, whereas R. Liu et al. (2019) acknowledge that 60 cycles of machine washing resulted in a median angular error of 34.1≪>$^{\circ}$. These disparate outcomes highlight the need for further investigation into the practicality.

Additionally, the number of participants in the studies varied considerably. Five system evaluations (Gupta et al., 2021; S. Hu et al., 2019; Y. Jin et al., 2020; Robinson et al., 2022; Ru et al., 2023) recruited only one participant, while eight studies recruited ten or more participants (X. Chen et al., 2022; Esfahani & Nussbaum, 2018; Gholami et al., 2019; R. Liu et al., 2019; Rezaei et al., 2019; Tavassolian et al., 2020; Vu et al., 2020; Zhu et al., 2021). As previously mentioned, the textile-sensing networks developed by Grassi et al. (2017) and Lau and Soh (2020) were designed to measure human flexion and extension movements, not a single particular joint. Therefore, no participants were recruited for accuracy evaluation in these three studies. Grassi et al. (2017) evaluated the performance of their network by putting it on a robot that could provide ground-truth knee joint angles, while the evaluation conducted by Lau and Soh (2020) was based on a simulated elbow joint. Furthermore, a prosthetic limb was used by Zou et al. (2023). Additionally, none of the studies for rehabilitation purposes recruited patients for evaluation, only health subjects were included.

3.2. Contextual matters in real scenarios

The focus of the 24 eligible studies was predominantly on technical considerations, while contextual matters were not the primary scope of their objectives. Only one study explicitly implemented the technology in a real-world context by integrating real-time angle monitoring with a robot designed to assist individuals with cognitive impairments in dressing (Robinson et al., 2022). While 16 other studies touched upon potential applications such as diagnostics, sports, robotics, and rehabilitation (X. Chen et al., 2022; Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Esfahani & Nussbaum, 2018; Gholami et al., 2018; Grassi et al., 2017; S. Hu et al., 2019; Y. Jin et al., 2020; Lau & Soh, 2020; R. Liu et al., 2019; Maselli et al., 2018; Mokhlespour Esfahani et al., 2017; Poomsalood et al., 2019; Rezaei et al., 2019; Totaro et al., 2017; Zhu et al., 2021; Zou et al., 2023), they did not explore in depth how their textile-sensing networks would operate within these settings. Additionally, eight studies delineated targeted scenarios: two were intended for running support (Gholami et al., 2019; Tavassolian et al., 2020), one for monitoring lumbar angles in astronauts to prevent lower back pain (Vu et al., 2020), and the remaining for rehabilitation

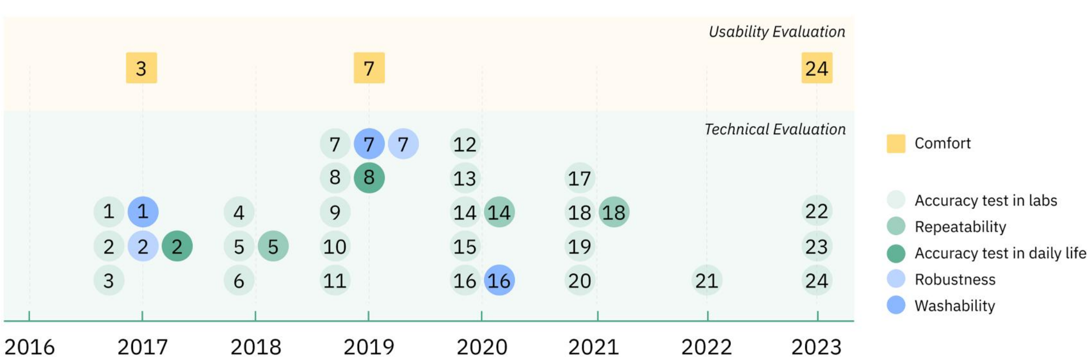

Figure 5. The schematic textile strain sensor placement strategies of the 24 eligible studies.

purposes(X. Chen et al., 2022; Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021; Gupta et al., 2021; Watson et al., 2020; Zou et al., 2023). Nevertheless, these studies largely omitted a thorough discussion of contextual design considerations.

Moreover, the majority of the studies focused primarily on users' physical characteristics, often neglecting aspects related to target users' perceptions, cognitive states, or subjective needs in real-life situations. With regard to wearable systems, while key features affecting the user experience – such as lightweight construction and comfort – were mentioned in most of the included studies, only a few engaged in substantive discussion or evaluation of these factors (X. Chen et al., 2022; Grassi et al., 2017; R. Liu et al., 2019).

4. Discussion

In this article, we offer a comprehensive review of wearable systems equipped with textile sensors for the continuous estimation of human joint angles in recent years. Utilizing a proposed framework that takes into account both technical and contextual considerations, we analyze 24 articles and identify two significant research gaps that merit further exploration.

The first research gap (Gap 1) concerns the disparity between advancements in textile-sensing systems for angle monitoring and the progress made in the field of textile strain sensors. During our PRISMA workflow, we found a substantial body of material science research ($n = 171$) focused on the development of versatile textile sensors capable of motion detection (Jiang et al., 2022; Z. Liu et al., 2022; L. Zhou, Shen, et al., 2022). These studies have confirmed excellent sensing performance by evaluating variations in output signals, such as resistance or capacitance, corresponding to different human motion angles. The large volume of these material science studies compared to the number of eligible articles ($n = 24$) highlights Gap 1, underscoring an evident disparity in this field.

The second research gap (Gap 2) underscores the need for wearable systems to be proficient not only in the technical aspects of textile-sensing networks for continuous angle estimation but also in addressing contextual considerations. These include application scenarios, wearability factors, and the subjective needs of users in real-world contexts. As discussed in the findings section, most of the systems developed in the eligible studies are still in a nascent prototype stage. Limited evaluation results are available concerning practicality or usability, apart from assessments of accuracy performance. Future research should aim to explore specific application scenarios and HCI interfaces that leverage this textile-sensing technology.

To present additional key insights, challenges, and discussions in this field, we draw upon studies from material science, computer science, HCI, as well as broader research in the human motion monitoring field. For example, although we excluded studies on human movement classification, such as those by Avellar et al. (2022); K. K. Kim et al. (2022); B. Zhou, Geissler, et al. (2022), because they did not meet our criteria for continuous joint angle capabilities, these studies could offer valuable insights for applications in wider contexts. To improve the organizational structure of our discussion, we have divided the content into three subsections: i) Developing Robust Textile-Sensing Networks, ii) Improving the Wearability of Wearable Systems, and iii) Expanding Application Scenarios for Continuous Joint Angle Monitoring with Textile-Sensing Networks. It is crucial to recognize that these subsections are not mutually exclusive but rather exhibit overlapping and interactive elements.

4.1. Developing Robust Textile-Sensing Networks

Textile-sensing networks are fundamental for textile-based wearable systems capable of continuously monitoring joint angles, which is a prerequisite for follow-up contextual applications. As shown in Figure 2, textile strain sensors, sensor placement, and algorithm were considered as three key matters for technical competent textile-sensing networks, and this subsection's primary focus is on these matters.

4.1.1. Consider suitable sensing characteristics for different monitoring purposes

While human joint angle measurement based on textile strain sensors is a material-driven research field, different types of sensor exhibit diverse features with regard to the key parameters of sensitivity, hysteresis, and linearity.

Resistive textile strain sensors are the most widely used sensors for predicting human movement. According to the findings provided by material science (Homayounfar & Andrew, 2020; X. Wang et al., 2022), they usually have high sensitivity. Recent advancements have amplified this characteristic even further. Specifically, Zhai et al. (2023) and Duan et al. (2023) have engineered sensors with remarkably high GF, attaining values of 1275 and 653.4, respectively. These developments underscore the escalating capability of resistive textile strain sensors to deliver increasingly sensitive measurements. However, their performance in hysteresis is relatively unsatisfied, and the linearity characteristic is prone to deterioration at high strain (Homayounfar & Andrew, 2020; X. Wang et al., 2022). Fortunately, effective solutions are being proposed to address the limitations of nonlinearity and high elastic hysteresis (Yang et al., 2017), and consequently contribute to consistent performance throughout the life cycle of sensors. Consequently, resistive sensors are anticipated to see broader application in future endeavors.

Compared to resistive sensors, capacitive strain sensors have relatively low sensitivity, but they offer high linearity and negligible hysteresis (S. Kim et al., 2017). It is noteworthy that some recent studies have been trying to address the limitation of low sensitivity and have achieved some progress. For example, X. Hu et al. (2022) developed a capacitive textile sensor with high sensitivity (GF = 2.07). Such improvement makes capacitive sensors being more suitable for measuring either small or large angles of body movement. In general, capacitive sensors are preferable considered for scenarios requiring high stability during long-term use. Futhermore, when it comes to the considerations of long-term use, another parameter, i.e., relaxation should be taken into account. Relaxation refers to the phenomenon where the readings of sensors do not remain constant under a fixed strain due to the loose connection of the textile's inner structure (X. Wang, Yang, et al., 2021).

In addition to aforementioned sensor types and parameters, researchers are supposed to remain sensitive to the latest advancements in fabric sensing technologies, as this may lead to the development of systems with higher accuracy and specialized sensing demands. For instance, despite the absence of piezoelectric textile sensors, they represent a promising future direction as they show self-power capabilities besides motion detecting (Babu et al., 2023; Fan et al., 2023; Wan et al., 2023). Tajitsu (2020) had developed a sensor using piezoelectric poly-l-lactic acid (PLLA) fibers sewn directly onto clothing for walking motion detection.

4.1.2. Consider more convincing strategies for textile sensor placement

The correlation between textile deformation and joint angles forms the foundational principle for estimating joint movements, making the location, number, and orientation of textile strain sensors crucial elements in textile-sensing networks. As the monitoring of joints with more complex movement features gains attention, the question of how to optimally position multiple sensors for a robust network becomes increasingly urgent. Researchers are moving towards more systematic approaches instead of relying solely on traditional, anatomically-based empirical methods. For example, Tormene et al. (2012) employed PCA to identify the most effective sensor placement for trunk movement detection. Currently, the most reliable method involves using optical motion tracking systems to pinpoint areas of maximum skin deformation during movement, thereby ensuring that the sensors are optimally stretched. This technique was first employed by Mattmann et al. (2007), using an optical motion tracking system to place 21 textile sensors on the back for upper trunk posture classification. The findings of this study have subsequently been cited in other works (Esfahani & Nussbaum, 2018; Rezaei et al., 2019), reinforcing its methodological importance. Sensor placements determined through this approach are considered to be more readily transferable to subsequent studies, and it is highly recommended for future research to consider utilizing this method. Furthermore, as demonstrated by X. Chen et al. (2022), the strategy of determining sensor placement based on calculating each sensor's effective monitoring area offers an insightful approach.

4.1.3. Towards more general and reliable angle estimation algorithms

Despite various types of sensors and placement strategies, the ultimate performance of angle estimation among eligible studies was comparable, which could be credited to algorithms. Although the selected studies achieved acceptable results in either of the two key constituents of the processing pipeline (i.e., data fusion and inference modeling), the implementation of more general and reliable angle estimation algorithms still faces evident limitations and challenges.

As for data fusion, only a few studies (Gholami et al., 2018, 2019; Tavassolian et al., 2020; Totaro et al., 2017; Vu et al., 2020) addressed this issue. The rest of the studies either achieved the task with a single sensor, which neglected the potential of multi-sensor fusion, or simply combined data from multiple sensors without applying any fusion techniques. However, both the selected studies in this review (Gholami et al., 2018; Tavassolian et al., 2020; Vu et al., 2020) and some recent studies (Padhy, 2021; PaPan et al., 2020; Qiu et al., 2022; Yuan et al., 2020) have demonstrated that data fusion at any level and any modality can boost the final performance. For instance, Yuan et al. (2020) performed feature-level fusion on data from multiple sensors to recognize sign language, which involves complex upper limb and finger movements. They used a deep CNN to extract shallow and deep features, representing global and local information respectively, and combined them for further modeling. They achieved an accuracy of 99.93%, demonstrating the potential of data fusion for complex human movement analysis.

As for the inference models, deductive approach is based on human anatomy and explores the relationship between kinematics and sensor deformation. This kind of method yielded acceptable and clear outcomes for joints with one-degree-of-freedom motions. However, the parameters of the equations require individual anthropometric data, which somewhat weakens the ease of widespread application of this method. By contrast, inductive methods are more reliable in all aspects, especially advanced machine learning methods such as NNs that outperforms other inductive methods. This can be attributed to the strength of NNs in handling non-linear data and their compatibility with vague data. For example, the ever-changing relative positions between sensors and target joints (X. Chen et al., 2022; S. Hu et al., 2019; Rezaei et al., 2019) and the deformation properties of the skin, such as elastic deformation, recovery, and skin laxity, may introduce unexpected variations into conventional inference models (X. Chen et al., 2022). However, NNs can handle these challenges with deeper layers, larger neural units or even transfer learning. This may also explain why different sensor characteristics can achieve comparable results.

However, the method of inductive models also has its drawbacks. For example, these models may overfit their training data, as shown by the errors in inter-subject and intra-subject results. This may impair the generalization ability of the proposed textile-sensing networks. To tackle this, researchers can use more training data from diverse subjects (Esfahani & Nussbaum, 2018; Mokhlespour Esfahani et al., 2017), or adapt models to each subject (Gholami et al., 2018, 2019). Moreover, a specific loss function in machine learning can guide models to consider these challenging factors and address these problems. For example, X. Chen et al. (2022) employed transfer learning techniques, specifically leveraging the MMD between distinct users, to achieve satisfactory outcomes. Such an approach provides a promising approach that future research could adopt to tackle similar challenges.

Nevertheless, irrespective of the model type employed, sensor aging remains an intractable issue due to the inherent variability in original input data and evolving patterns. Several methodologies have been proposed to address this challenge. For example, X. Chen et al. (2024) deployed average pooling layers and a min pooling layer to assess and calibrate shifting baselines. Zhu et al. (2021) implemented a loss function designed to quantify the estimation discrepancy between aging and new sensors, with which the inference model will minimize this variance by learning common patterns discernible in both sensor types.

4.2. Improving the wearability of wearable systems

Wearability, defined as the interaction between wearable objects and the human body, significantly impacts user experience and acceptability (Gemperle et al., 1998). Beyond fundamental prerequisites such as lightweight construction and comfort, which are integral to the user's experience with wearables, additional factors pertaining to the system's practical utility warrant consideration. These include methods of integration, power management, and washability. In the following subsection, we offer a comprehensive discussion and provide recommendations aimed at enhancing wearability.

According to the classification by Seymour (2008), the levels of integration for wearable prototypes can be categorized into three distinct types: attachable, embedded, and integrated. In the majority of studies examined, textile sensors were either physically mounted or embedded into preexisting textile substrates, typically through methods such as adhesion or sewing. These approaches predominantly result in lower degrees of integration, falling under the categories of either attachable or embedded. Two primary concerns arise from these methods of integration. First, the comfort of the wearer may be compromised, as the fixation techniques employed can adversely affect the flexibility and stretchability of the substrate material. Second, the potential for misalignment between the textile sensors and the substrate could introduce inaccuracies in monitoring outcomes, thereby undermining the sensor's performance. However, advancements in dimensional compatibility (Hwang et al., 2022) have enabled the integration of fibers, yarns, and fabrics into non-conductive materials through textile fabrication techniques such as embroidery and knitting. Consequently, a higher level of integration in wearable systems is anticipated. For instance, the knee pad developed by Gupta et al. (2023) for monitoring knee joint motion utilized stretchable textile sensors and exemplified an integrated-level system.

Regarding power considerations, the sensing networks described in the relevant literature generally operate under the assumption of a readily available power source. Conventional approaches, such as connection to an electrical grid or the inclusion of a battery system, may negatively impact the device's wearability. To mitigate these challenges, alternative solutions such as piezoelectric textile sensors (Wan et al., 2023) and power-generating textiles should be considered. For instance, research by M. Li et al. (2021) has contributed to this area by developing flexible fiber-based Zn-ion batteries with a high energy density of 36.04 $\ll > mWh/cm^3$. Notably, these fibers demonstrate considerable stretchability (up to 900%) and bending capacity (ranging from 0 to 180 degrees), indicating their potential for seamless integration into textile substrates. These advancements offer valuable insights into the feasibility of creating an integrated system that combines textile sensors, power sources, and substrates in a unified manner.

It is important to acknowledge that higher levels of integration may compromise the ease of component replaceability. One potential solution to this challenge is the incorporation of sensors into detachable components, as evidenced in studies where textile strain sensors were affixed to substrates using metal snaps or buttons (Di Tocco, Carnevale, Bravi, et al., 2021; Di Tocco, Carnevale, Presti, et al., 2021). While this method of attachment facilitates both sensor replacement and substrate washability, it may introduce measurement inaccuracies if the sensors are not in direct contact with the substrate. In summary, a myriad of integration methods exist in the literature, and the selection among them should be predicated on the specific objectives and potential application contexts of each study.

Additionally, the aspect of washability, which significantly contributes to the practical utility of wearable systems, has been largely neglected in the studies under consideration. However, it is noteworthy that a growing body of research in material science has begun to address this issue (Duan et al., 2023; M. Li et al., 2022; Z. Li et al., 2021). For example, a study by M. Li et al. (2022) introduced a fiber-based Zn battery rescue rope that displayed remarkable resilience under extreme conditions of fire and water exposure. In a similar vein, research by Duan et al. (2023) presented a stretch-tolerant, super-hydrophobic strain sensor with exceptional water-resistant properties. These advancements in sensor technology provide promising directions for incorporating washability considerations in future research.

4.3. Expanding application scenarios

According to the findings, the developed wearable systems showed acceptable accuracy for continuous joint angle monitoring. However, the research gap 2 indicated that most of the systems were still in a primitive prototype stage. It is not yet clear in which specific application scenarios these systems could be further leveraged. By combing the insightful literature in both motion monitoring and HCI fields, as shown in Figure 6, some promising application domains were discussed in this subsection.

4.3.1. Textile-based human motion measurement may be the new growth point of rehabilitation medicine

Rehabilitation-related applications have long been a primary focus of wearable systems for human movement monitoring, as noted in multiple studies (M. Chen et al., 2017; McLaren

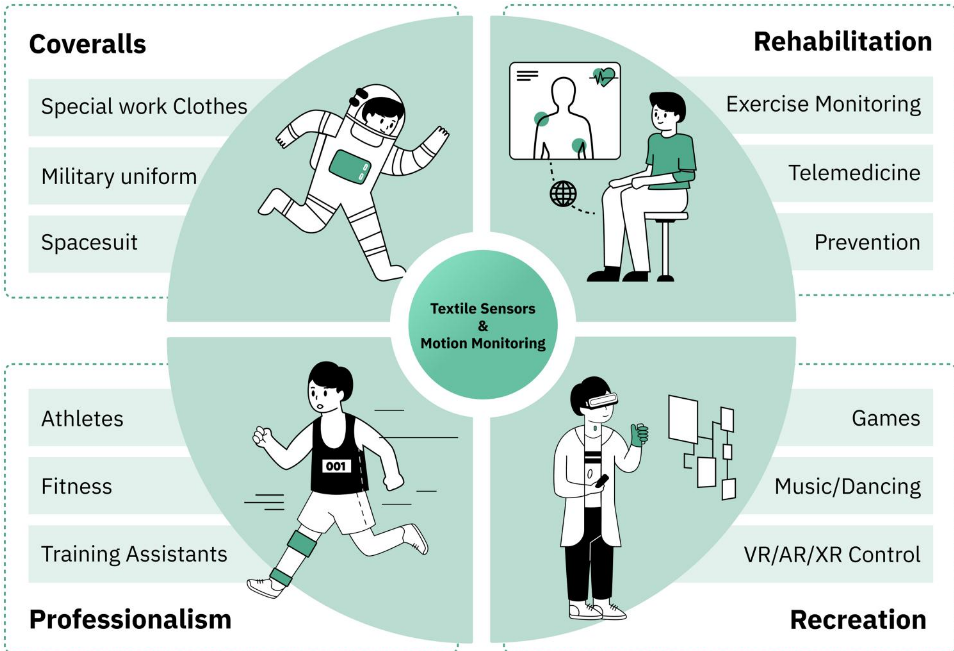

Figure 6. Illustration of possible application scenarios for future research.

et al., 2016; Semjonova et al., 2020). Insights from studies aimed at human activity classification, applied in a wide range of scenarios like gait recognition for rehabilitation (Wei et al., 2023) and sports rehabilitation (Tolba & Al-Makhadmeh, 2020), support this focus. Given that the studies we included demonstrate the potential of textile-sensing wearables for continuous joint angle estimation, the timing is ideal for HCI researchers to incorporate these textile sensors into actual rehabilitation or medical settings for usability and clinical performance assessment. On one hand, in-depth collaboration with clinical experts could benefit common rehabilitation scenarios such as stroke-induced physical dysfunction and musculoskeletal injuries. These conditions could be better managed through real-time monitoring of abnormal movements using textile-sensing networks. On the other hand, the high flexibility and low intrusiveness of textile sensors offer a higher comfort level, which is especially important in a rehabilitation context. This technology also addresses psychological needs of patients, including privacy concerns and self-esteem.

4.3.2. Elegant interactive interfaces for professionalism and recreation are expected

As a large number of studies from material science, HCI and engineering have demonstrated the versatility of textile sensors across various scenarios (Xu et al., 2023), the technology for continuous joint angle estimation, based on textile-sensing networks, also holds great promise. For wearable scenarios, it has potential applications in a wide range of areas including special occasion coveralls, professional sports, entertainment and. Despite the limited number of application cases in eligible studies, research focusing on human activity classification has garnered significant attention and could offer valuable insights (Q. Liu et al., 2023). For example, MIT Media Lab (Tibbits, n.d.) explored how to use textile strain fibers in spacesuits to monitor astronaut's elbow movement. In the entertainment industry, Liang et al. (2021) developed a smart dance leotard based on fabric sensors that assists dancers with their movements, while Greinke et al. (2021) designed a jacket that detects the conductor's movement to improve orchestra performances. On the other hand, beyond wearables, more interactive interfaces based on joint angle monitoring are expected to emerge, including those in popular HCI research fields, such as intelligent cockpit, smart home, artistic expression (Tepe et al., 2023), mixed realities (XR)(Wen et al., 2020).

4.3.3. Further usability and clinical evaluations deserve more attention

The included studies primarily focused on technical evaluations and did not provide tangible or perceptible feedback for end-users, making it challenging to conduct usability evaluations with participants. However, as joint angle estimation research expands into wider application scenarios, clear and effective feedback will become a prerequisite for evaluating wearable systems in real-world scenarios, allowing participants to better interact with wearable systems and provide valuable insights for researchers. Miniature displays, wearable actuators, or mobile phone apps are traditional feedback modules that can be incorporated into wearable devices or separate devices. Besides, the textile-based feedback modules are also worth considering (J. Shi et al., 2020), such as luminous fibers (Olwal et al., 2018), thermochromic fabrics (Q. Wang, Ye, et al., 2021), and knitted textile vibration modules (J. H. Kim et al., 2022), etc.

Once the system is capable of feedback, there is the possibility of further evaluation. As also suggested in an earlier review relating to e-textiles and rehabilitation (McLaren et al., 2016), in the realm of wearable systems for rehabilitation, it is crucial to conduct further usability and clinical testing to ensure their efficacy. To enhance the credibility of these systems, evaluations should involve patients undergoing rehabilitation training. Additionally, the participation of physiotherapists in evaluation sessions can provide valuable advice and guidance for researchers to iterative and improve the system. It is important to note that limited testing time may introduce bias in the results. Long-term evaluation, on the other hand, can help analyze the monitoring performance of the system and provide insights into the wearability and lifespan of the wearable systems.

5. Conclusion

In this systematic review, 24 eligible wearable systems equipping with textile strain sensors for continuous human joint angle estimation were analyzed with the proposed framework. The findings suggested that the existing textile-sensing networks were capable for monitoring most parts of the body's continuous joint angles with satisfactory accuracy, but there were still challenges in terms of both technical and contextual matters. On one hand, more compact collaborations among experts from different disciplines are expected for textile-sensing networks building, including applying textile sensors that show better performance, employing more convincing sensor placement strategies, and constructing more robust algorithms. On the other hand, these studies only made superficial references to possible application targets, and there was still a lack of in-depth research or application demonstrations based on pathological or psychological disorders. Vast application scenarios like rehabilitation, professional athletics, and entertainment, and also the usability evaluation in these cases are to be explored. Overall, this paper examined wearable systems for continuous human motion estimation based on textile sensors, using a new proposed framework. We do hope the findings, discussions, and insights presented could benefit more researchers to contribute to diminishing the existing research challenges mentioned in this field.

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