The following publication H. Hu, X. Shi, W. Song, Y. Yang and J. Zhang, "Research Progress of Intelligent Sitting Posture Monitoring Systems: A Survey," in IEEE Transactions on Instrumentation and Measurement, vol. 74, pp. 1-23, 2025, Art no. 9527923 is available at https://doi.org/10.1109/TIM.2025.3588986.

Research Progress of Intelligent Sitting Posture Monitoring Systems: A Survey

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***Abstract*—Sitting posture monitoring is a crucial aspect of health management, offering significant long-term benefits for individual well-being and public health. This paper provides a state-of-the-art survey of intelligent sitting posture monitoring systems, which leverage advanced sensors and algorithms to deliver real-time feedback and promote healthier sitting habits. The survey uniquely integrates the four critical stages in the design of such systems: data capture, dataset establishment, model construction, and system feedback. Unlike previous fragmented research on isolated aspects, this work addresses the full pipeline, bridging the gap in holistic guidance for establishing intelligent posture monitoring systems. It also summarizes commonly used commercial sensors to guide researchers and practitioners in selecting appropriate solutions for posture monitoring. This comprehensive survey of current methodologies identifies key research gaps and proposes directions for future work to advance health management through the improvement and broad application of intelligent sitting posture monitoring systems.**

***Index Terms*—Intelligent system; sitting posture monitoring; sensors; data analytics; system feedback**

I. Introduction

WITH lifestyle changes and technological advancements, people are spending increasingly more time in a sitting posture. Statistics indicate that adults sit for an average of 8.2 hours per day [1]. Prolonged sedentary behavior, typically sitting for more than six hours per day, has been associated with an elevated risk of developing 12 chronic non-communicable diseases [2], including diabetes [3], [4] and cardiovascular disease [5], [6] among others. Additionally, poor sitting posture can further aggravate health issues, contributing to chronic conditions such as low back pain [7]–[11] and neck pain [12]–[15]. Consequently, the continuous monitoring and analysis of sitting postures has become a critical component of health management.

Traditional posture monitoring methods, such as manual observation and self-reported questionnaires, often produce unreliable results [16]. Advances in sensor technology and artificial intelligence have led to the emergence of intelligent sitting posture monitoring systems as an innovative solution [17]–[19]. These systems capture, analyze, and provide real-time feedback on users' postures, promoting healthy sitting habits and mitigating health risks associated with prolonged sitting and poor posture. Such systems have found extensive applications across various domains, including workplace health management [20]–[22], human activity recognition [23]–[25], pressure ulcer prevention for wheelchair users [26]–[29], spinal posture analysis [30]–[33], educational environments [34], [35], elderly care [36]–[38], and posture recognition and fatigue detection in driving scenarios [39], [40]. Their widespread use not only enhances individual awareness of healthy postures but also contributes significantly to public health management.

Therefore, the development of efficient and accurate intelligent posture monitoring systems remains a critical priority.

The development of intelligent sitting posture monitoring systems spans multiple disciplines, including ergonomics, sensor technology, computer science, and psychology. This interdisciplinary field is pivotal for advancing technological innovation and promoting knowledge integration. Existing research has largely focused on isolated stages such as data collection techniques, posture detection, and classification strategies [41]–[46]. However, these studies fail to comprehensively explore the pipeline from data acquisition to user feedback, particularly in terms of system feedback, which is crucial for enabling real-time monitoring and behavioral modification. Moreover, there is a lack of systematic summaries on the commonly used sensors, diversity of datasets, and AI models for posture classification, limiting the comprehensiveness and adaptability of monitoring systems, as shown in Table I.

To address these gaps, this survey presents a comprehensive survey of the pipeline for developing intelligent sitting posture monitoring systems (Fig. 1). The pipeline consists of four main stages: (1) data capture, utilizing various sensor types, including non-contact sensors [20], [47]–[49], low-contact sensors [50]–[54], high-contact sensors [55]–[58], and multi-sensor systems [18], [59], [60] (Section II); (2) dataset establishment, focusing on participant diversity, posture categories, and chair types [27], [61] (Section III); (3) model construction, encompassing data preprocessing, feature extraction, and posture classification [22], [62], [63] (Section IV); and (4) system feedback, incorporating visual [51], [64], tactile [65], and auditory [62], [66] feedback methods (Section V). Finally, the survey provides a comparative analysis of existing methodologies, discusses current limitations, and highlights potential directions for future research (Section VI). The main contributions of this survey are as follows:

- We have presented a pioneering effort in offering a state-of-the-art survey on the most comprehensive pipeline for

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This research was supported in part by grants from the Guangdong Province philosophy and social science planning project (No. GD24YYS04), the Basic and Applied Basic Research Foundation of Guangdong Province (No. 2022A1515110652), the Start-up Fund for New Recruits of the Hong Kong Polytechnic University (No. P0049603), and the Macao Polytechnic University (No. RP/FCA-03/2024).

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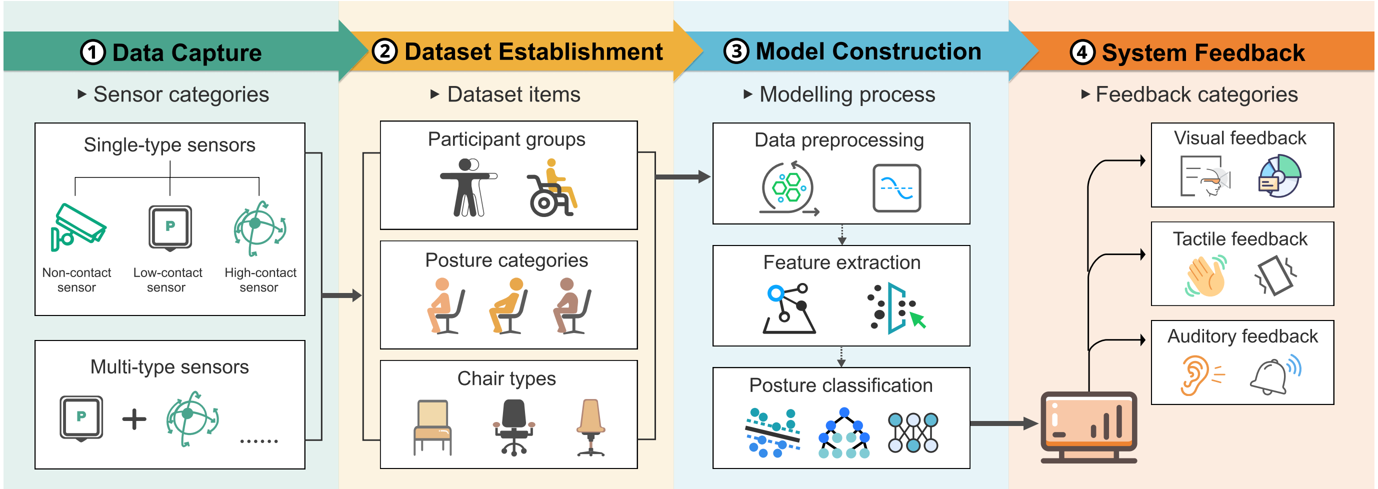

Fig. 1. Summarized pipeline of intelligent system establishment for sitting posture monitoring. The procedure consists of 4 steps: (1) data capture, using single-type sensors such as non-contact sensors [20], [47]–[49], low-contact sensors [50]–[54], high-contact sensors [55]–[58], or multi-type sensors systems [18], [59], [60], (2) dataset establishment [27], [61], which includes participant groups, captured posture categories, and chair types, (3) model construction [22], [62], [63], involving data processing, feature extraction, and posture classification, and (4) system feedback, which primarily includes visual [51], [64], tactile [65], and auditory [62], [66] feedback.

TABLE I
COMPARATIVE ANALYSIS OF SURVEYS. NOTE THAT OUR SURVEY INCLUDES THE MOST COMPREHENSIVE PIPELINE FOR ESTABLISHING INTELLIGENT SITTING POSTURE SYSTEMS.

Study	Publication	Data Capture		Dataset Establishment			Model Construction			System Feedback			Holistic
	Year	Sensor Types	Sensor Configurations	Participant Groups	Posture Categories	Chair Types	Data Preprocessing	Feature Extraction	Posture Classification	Visual	Tactile	Auditory	Pipeline
Tlili et al. [41]	2018	✓											
Kappattanavar et al. [42]	2021	✓		✓	5				✓				
Gonzalez et al. [43]	2024	✓		✓	7				✓				
Vermander et al. [44]	2024	✓							✓				
Odesola et al. [45]	2024	✓	✓	✓	20				✓				
Krauter et al. [46]	2024	✓								✓	✓	✓	
Ours		✓	✓	✓	37	✓	✓	✓	✓	✓	✓	✓	✓

establishing intelligent sitting posture systems. This interdisciplinary framework contributes to ergonomics engineers designing ergonomic products, clinical researchers developing spinal rehabilitation protocols, IoT engineers optimizing sensor fusion architectures, and intelligent algorithm developers optimizing pose recognition models.

- We have summarized the most extensive sitting posture categories monitored by intelligent systems, making it possible to set a uniform standard for future sitting posture classification.
- We have compiled a catalog of commercial sensors along with their corresponding links, serving as essential resources for academic researchers such as medical device engineers, industrial system designers, and AI hardware developers seeking to replicate and innovate within their studies.

II. DATA CAPTURE

The initial stage in developing an intelligent sitting posture monitoring system is data capture, which involves collecting data on various sitting postures using appropriate monitoring devices. Sensors used in such systems are categorized based on their level of contact with the user's body: non-contact sensors (no physical contact), low-contact sensors (intermittent contact), and high-contact sensors (full contact), as shown in Fig. 2. Fig. 3 further details the specific sensor types within each category and their applications in posture monitoring systems.

A. Non-contact Sensors

Non-contact sensors in intelligent monitoring systems monitor sitting posture without direct physical contact. These systems mainly rely on vision-based technologies and distance-

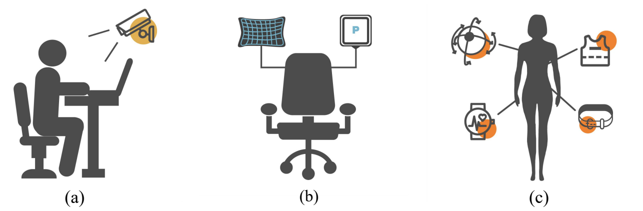

Fig. 2. Sensor categories in intelligent systems for sitting posture monitoring. (a) Non-contact sensors (no direct contact with the user, dominated by camera-based vision sensors) [20], [47]–[49], (b) low-contact sensors (intermittent contact with the user, dominated by pressure sensors) [50]–[54], and (c) high-contact sensors (full contact with the user, dominated by wearable sensors) [55]–[58].

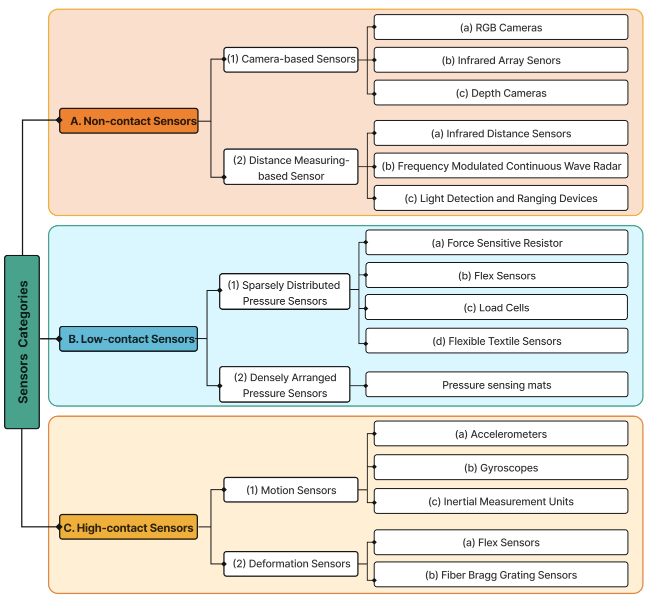

Fig. 3. Sensor types within three categories used in intelligent sitting monitoring systems.

measuring sensors (see Table II). Additionally, acoustic sensing via smartphones has been explored for posture recognition [67].

Non-contact sensors are generally simple and non-intrusive, making them advantageous for many applications. However, vision-based sensors, such as cameras, raise significant privacy concerns, underscoring the importance of addressing data protection and ethical considerations in system design [20], [59], [68].

*1) **Camera-based Sensors**:* Camera-based sensors play a pivotal role in posture monitoring by providing real-time image data for computer vision systems to analyze sitting posture. These sensors identify key reference points on the human body, such as the head, shoulders, arms, and hips [59]. By analyzing the relative positions of these points, they estimate posture and can simultaneously monitor multiple individuals within their field of view [69]. Proper camera placement, such as positioning at eye level or slightly higher, is critical for avoiding body part obstructions and ensuring comprehensive posture capture. Common setups include frontal [20], [34], [49], [62], [63], [70], [71], lateral [61], [72], [73], or combined front-lateral views [47].

a. RGB Cameras. RGB cameras capture images in red, green, and blue channels, offering a cost-effective and widely accessible solution for posture monitoring [47]. These cameras are easy to install and do not require complex hardware configurations [46]. However, their performance is highly dependent on environmental factors such as lighting and background conditions, which can affect image quality and posture detection accuracy [44]. Due to their limitations in recognizing complex poses, RGB cameras are less effective for detailed posture analysis.

b. Infrared Array Sensors. Infrared array sensors detect posture by capturing thermal radiation emitted by the body, generating thermal images that reflect surface temperature distribution [20], [59]. This method is robust against lighting conditions and enhances privacy by avoiding the capture of external physical features [59], [74]. However, its accuracy depends on factors like object emissivity and ambient temperature, leading to varying performance indoors versus outdoors [44]. Additionally, the low resolution of thermal images reduces their clarity, limiting the effectiveness of these cameras for precise posture monitoring.

c. Depth Cameras. Depth cameras measure the distance between body key points and the sensor to create a 3D point cloud model for posture analysis. These cameras are versatile, functioning effectively under varying lighting conditions and capturing highly detailed data, including depth maps and point clouds. Depth cameras such as the Microsoft Kinect [48], [61], [69], [73], [76] are widely used for applications including human-computer interaction [36], motion capture [77], and pose recognition [34], [61], [78]. For optimal performance, depth cameras must be mounted to avoid environmental obstructions that interfere with capturing skeletal data.

While Kinect excels in accuracy and privacy protection by avoiding image or video capture [48], it has high hardware requirements, limiting its use in embedded systems. Alternatives like the Astra 3D sensor support multiple operating systems, including Windows, Linux, and Android, offering more flexibility [63]. Additionally, the Onion Tau LiDAR camera, despite its lower resolution, is a simple and cost-effective option for sitting posture monitoring [79].

*2) **Distance-measuring Sensors**:* Distance-measuring sensors capture postural information by measuring changes in the distance between the body and the sensor. Unlike camera-based sensors, these devices do not capture images but instead provide precise distance measurements.

a. Infrared Distance Sensors. Infrared distance sensors measure distances by emitting and receiving infrared light. These sensors are highly resistant to interference and are characterized by their compact design and integration capabilities [80], [81]. The emitted infrared beam reflects off the target object, and the sensor calculates the distance based on parameters such as reflection angle, time of flight, or light intensity. For instance, these sensors can monitor the distance between a user's head and a desktop in real-time, offering valuable data to identify posture deviations [62]. Their simplicity and real-time capabilities make them suitable for

TABLE II
Comparisons of non-contact sensors commonly used in human sitting posture monitoring systems.

Sensor Type*		Product	Company	Price ($)	Measuring Range	Accuracy	Studies
Camera-based	RGB	A4Tech PK-635M webcam[a]⋆	A4Tech	-	-	-	[47]
	Infrare Array	MLX90640 infrared array sensor[b]	Melexis	42.49	-40-300 °C	±1 °C	[20]
	Depth	Kinect	Microsoft	-	0.5-4.5 m	-	[61], [69]
	Depth	Astra 3D sensor[c]	Orbbec	-	0.6-8 m	≤0.3 %	[63]
Distance-measuring	Infrared	GP2Y0D02YK0F infrared proximity sensor[d]	Sharp Corporation	10-20	0-0.8 m	-	[62], [75]
	Radar	FMCW radar	-	-	-	-	[49]
	Lidar	LiDAR	-	-	-	-	[70]

*In the "product" section, products marked with "⋆" indicate that the product is no longer in production.

[a] https://www.a4tech.com/products.aspx?id=5

[b] https://www.melexis.com/zh/product/MLX90640/MLX90640

[c] https://www.orbbec.com.cn/

[d] https://www.sharpsde.com/products/model/GP2Y0D02YK0F/

monitoring applications, though their performance may be influenced by environmental conditions.

b. Frequency-modulated Continuous Wave (FMCW) Radar. FMCW radar transmits frequency-modulated signals and analyzes the returned signal to measure both the distance and speed of the target. By detecting time delays and Doppler shifts, these sensors provide high accuracy and are unaffected by lighting conditions, making them ideal for non-contact posture detection [49], [82]. Their wireless operation enhances user comfort and ensures privacy protection, further broadening their applicability in human activity recognition and posture monitoring.

c. Light Detection and Ranging (LiDAR) Devices. LiDAR measures distances by emitting laser pulses and recording the time taken for their return. This data is processed to generate detailed 3D point cloud models for precise posture analysis [83]. While traditional LiDAR systems are often bulky and expensive, recent advancements have introduced compact and cost-effective designs [70]. These newer systems prioritize portability and privacy, allowing for seamless integration into posture monitoring applications with minimal setup requirements.

B. Low-contact Sensors

Low-contact sensors activate and collect data when the user physically interacts with them. The most commonly used are pressure sensors, typically integrated into the seating surface [9], [51], [52], [54], [65], [84]–[86], backrest [23], [25], [27], [54], [87]–[89], and armrests [90], [91] of chairs, forming a "smart chair" system [18]. These systems monitor body pressure distribution using strategically placed sensors, where applied external forces alter the conductive network, causing measurable changes in resistance [21], [51], [92], capacitance

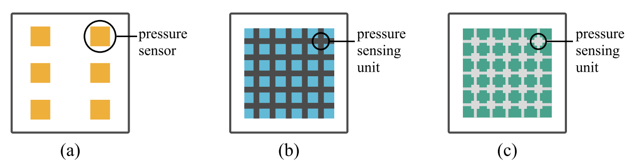

Fig. 4. Schematic diagram of the configuration of sparsely distributed pressure sensors and densely arranged pressure sensors. (a) Sparse distribution: each pressure sensor is strategically placed at intervals within the monitoring area to detect pressure changes at various locations [21], [51], [53], [91], [96], [100]–[102], [107], [108]. (b) Dense grid structure: conductive electrodes intersect to form a grid, with each intersection point acting as an individual pressure sensing unit [9], [16], [50], [65], [86], [103]–[105], [109]. (c) Dense array structure: pressure sensing units, connected by conductive electrodes, are arranged in a specific row-by-column format to create a uniformly distributed pressure monitoring area [89], [110].

[54], or voltage [16], [64]. Alternatively, there are optical fiber sensors [93] and temperature sensors [94] for posture control.

Pressure sensors are generally available in two configurations (Fig. 4): sparsely distributed small sensors and densely arranged pressure sensors. Table III summarizes the commonly used low-contact sensors in research.

Unlike camera-based sensors, low-contact sensors do not capture images, making them both non-intrusive and portable. However, they are less effective at detecting subtle posture changes, such as those involving the head or upper body [18], [59], limiting their scope in comprehensive monitoring.

*1) **Sparsely Distributed Pressure Sensors:*** Sparsely distributed pressure sensors are arranged in widely spaced patterns across the monitoring area to detect body posture or contact by measuring localized pressure changes. Typically comprising a few to several dozen sensors, each outputs pressure data from a specific location. The system then infers overall pressure distribution based on variations in these

TABLE III
COMPARISON OF LOW-CONTACT SENSORS COMMONLY USED IN HUMAN SITTING MONITORING SYSTEMS.

Sensor Type*		Product	Company	Price ($)	Measuring Range	Sensing Area (mm)	Accuracy	Studies
Sparsely distributed pressure sensors	FSR	Force sensing resistor 406[a]	Interlink Electronics	3.99-4.99	0.2-150 N	38.1×38.1	-	[29], [95] [96], [97]
	FSR	Force sensing resistor 402[a]	Interlink Electronics	2.99-3.99	0.2-150 N	12.70 (ϕ)	-	[60]
	FSR	Force sensing resistor 400[a]	Interlink Electronics	2.99-3.99	0.2-150 N	4.06 (ϕ)	-	[26]
	FSR	FlexiForce A201[b]	Tekscan	19.15	0-445 N	9.53 (ϕ)	$\leq \pm 3\%$	[52]
	FSR	FlexiForce A502[c]	Tekscan	27.82	0-222 N	50.8×50.8	$\leq \pm 3\%$	[98]
	FSR	FSR01CE[d]	Ohmite	10-17	0.2-50 N	39.7×39.7	-	[53]
	FS	FS-L-055-253-ST	Spectra Symbol	9.99	0-55.37 mm	-	-	[91]
	LC	P0236-I42	Hanjin Data Corp.	-	-	-	-	[99], [100]
	LC	FX1901-0001-0100-L[e]	TE Connectivity	21-37	1-100 lbf	-	$\leq \pm 1\%$	[101]
	FTS	W-290-PCN type conductive textile[f]	Ajin-Electron	-	-	-	-	[102]
Densely arranged pressure sensors	PSM	Body pressure measurement system BRE5315[g]	Tekscan	-	0-34 kPa	488.7×426.7	$\leq \pm 10\%$	[50], [103] [104]
	PSM	Sensomative science[h]	Sensomative GmbH	-	1-100 kPa	350×350	-	[105]
	PSM	IMM00014	I-MOTION	-	-	305×364	-	[65]
	PSM	Xsensor LX100:40.64.02[i]	XSENSOR Technology	-	7-270 kPa	510×810	$\leq \pm 5\%$	[106]
	PSM	Xsensor LX100:40.40.02[i]	XSENSOR Technology	-	7-270 kPa	510×510	$\leq \pm 5\%$	[106]

*The following notations are also used: "FSR" for force sensitive resistor, "FS" for flex sensor, "LC" for load cell, "FTS" for flexible textile sensor, and "PSM" for pressure sensing mat.

[a] https://www.interlinkelectronics.com/force-sensing-resistor

[b] https://www.tekscan.com/products-solutions/force-sensors/a201

[c] https://www.tekscan.com/products-solutions/force-sensors/flexiforce-a502-sensor

[d] https://www.ohmite.com/catalog/fsr-series/FSR01CE

[e] https://www.te.com/en/product-FX1901-0001-0100-L

[f] http://www.ajinelectron.co.kr/bbs/board.php?bo$_t$able=sub02$_0$1$_c$hn

[g] https://www.tekscan.com/products-solutions/systems/body-pressure-measurement-system-bpms

[h] https://sensomative.com/de/produkte/sensomative-science/

[i] https://www.xsensor.com/solutions-and-platform/design-and-safety/seating-ergonomics

localized readings. This arrangement is cost-effective, making it a more accessible solution for posture monitoring.

In recent years, there has been growing interest in using small, unobtrusive sensors for sitting posture recognition [44]. However, these sensors are limited to measuring pressure in specific areas and are generally suited for lower-resolution monitoring. Achieving accurate posture recognition while minimizing hardware costs requires careful consideration of sensor placement. Current research identifies two main approaches to optimizing placement:

- Mathematical and Statistical Methods: This approach uses computational techniques to determine near-optimal sensor configurations [97], [111]. For instance, one study achieved superior classification accuracy using only 31 sensors out of 4032 potential positions, outperforming both random and uniform placement strategies [97].
- Anatomy-Based Placement: This method relies on anatomical knowledge to position sensors at key body regions, such as the sciatic tuberosity, thighs, lumbar region, and scapula [112]–[114]. This approach is widely adopted in existing studies due to its practicality and alignment with human biomechanics.

While both methods offer advantages, anatomical placement is more prevalent in current research, reflecting its effectiveness in capturing critical pressure points for posture monitoring.

a. Force Sensitive Resistors (FSR). FSRs are widely used sparsely distributed pressure sensors, functioning as variable resistors whose resistance decreases with increasing pressure [21], [26], [29], [51], [53], [95]–[97], [107], [108]. These sensors operate by connecting in series with a pull-down resistor in a circuit where a reference voltage is applied. As pressure increases, the output voltage rises, which is detected and converted into an analog signal via a microcontroller and an analog-to-digital converter [115]. The pull-down resistor's value significantly influences the voltage-pressure relationship, and most studies use 10 KΩ resistors for optimal performance [115]. Common FSR models include the square 406 series [29], [95]–[97], the round 402 series [60], and the 400 series [26] from Interlink Electronics.

FSRs are compact, lightweight, and flexible, enabling them to conform to complex surfaces and environments. However, they require placement on rigid surfaces for accurate readings. Assembly can be challenging, often involving multiple wires and microcontrollers, necessitating careful management to prevent crosstalk. Moreover, traditional assembly methods are not easily adaptable across different seating configurations. To address this, some studies have integrated FSRs into portable cushions, enhancing their versatility for various chair types [25], [52], [116], [117].

b. Flex Sensors (FS). FSs consist of polymer ink with conductive particles layered on a plastic sheet. When the sensor bends, the distance between conductive particles changes, resulting in resistance variations [91]. These sensors are typically connected to a resistor in a voltage divider configuration, converting resistance changes into corresponding voltage signals. Their simplicity and flexibility make them useful for applications where bending or angular measurements are required.

c. Load Cells (LC). LCs convert mechanical forces into electrical signals by altering the strain gauge resistance inside the sensor, disturbing the Wheatstone bridge's equilibrium and producing a voltage signal. Known for their accuracy and stability under high forces or weights [118], LCs typically feature rigid metal structures, making them suitable for high-precision applications. In posture monitoring studies, LCs are often placed under removable cushions [99], [100] or housed in 3D-printed cases integrated into chair frames [101]. Despite their precision, their size and rigidity make them less portable and adaptable compared to other sensors.

d. Flexible Textile Sensors (FTS). FTSs are made from conductive fabrics that detect pressure by converting physical changes into electrical signals. These sensors have gained popularity due to their high conductivity and adaptability [102]. They are commonly integrated into cushions and capacitive sensor mats, where force variations are detected as changes in capacitance [102], [119]. FTSs are lightweight, soft, and user-friendly, enhancing comfort during prolonged use. However, their performance degrades with repeated bending or prolonged use, and they are highly sensitive to environmental factors such as humidity and temperature, leading to signal instability.

*2) **Densely Arranged Pressure Sensors**:* Densely arranged pressure sensor arrays consist of multiple sensing units typically organized in a matrix configuration. Pressure sensing mats (PSMs) are the most common implementation, with arrays ranging from 196 to over 2000 sensing units [9], [50], [65], [105], enabling high-resolution pressure mapping. Unlike sparsely distributed systems, where each sensor outputs data independently and requires separate wiring, densely arranged arrays simplify connectivity and data transfer. These systems aggregate data from multiple sensing units and transmit it through a single interface, significantly improving data collection efficiency and system integration.

Many commercial PSMs, such as the Body Pressure Measurement System (BPMS) by Tekscan [50], [103], [104] and XSENSOR [106], are equipped with specialized software for precise data acquisition and processing. Despite their high resolution and integration capabilities, these systems are often expensive, limiting their widespread adoption.

To address this issue, recent research has focused on developing cost-effective posture-monitoring sensors using advanced materials and fabrication techniques. For instance, graphene composites [109], multilayer MXene/cellulose nanofibers [110], and knitted sensor fabrics combined with electrode materials [86] have been explored to create affordable alternatives with high sensitivity and flexibility.

C. High-contact Sensors

High-contact sensors, often referred to as wearable sensors, are designed to maintain full contact with the user's body, enabling real-time monitoring of physiological and environmental parameters. These systems primarily use two sensor categories: motion sensors and deformation sensors. Other types include wearable radio frequency identification (RFID) tags [120] and ultrasonic sensors [121]. Table IV provides a summary of high-contact sensors commonly used in research.

Proper placement of wearable sensors is crucial for accurate data collection. Sensors are often placed along the spine [55], [122]–[126], particularly between the C7 and L4 vertebrae, to estimate sitting posture with high precision [127]. Other placement areas include the shoulder [57], [66], [128], [129], chest [129], and arm regions [130]. Depending on the application, sensors can be attached directly to the skin or clothing [55], [122], [126], [130], secured to a belt or vest [57], [66], [123], [125], [131], or integrated into garments [129], [132].

While offering portability and low cost [44], prolonged wear may affect user comfort due to skin contact [20], [123], [133].

*1) **Motion Sensors**:* Motion sensors detect changes in body motion and posture by measuring parameters such as acceleration, angular velocity, and orientation in three-dimensional space. These sensors typically operate on internal microelectromechanical systems (MEMS). However, most commercially available motion sensors are encased and require a complex calibration process before use [122].

a. Accelerometers. Tri-axial accelerometers measure acceleration changes along the X, Y, and Z axes, providing data on the object's motion state in three-dimensional space. They are widely used in applications such as routine activity quantification [135], scoliosis physiotherapy [136], [137], and postural analysis [138], [139]. Studies often use accelerometers to measure tilt angles in the sagittal and coronal planes of the spinal axis system, enabling the identification of sitting postures such as upright, forward-leaning, backward-leaning, or side-leaning positions [66], [122].

A single accelerometer can assess trunk tilt in multiple directions, although it cannot detect spinal curvature changes without reference signals from distal spinal segments [122]. Using multiple accelerometers improves the resolution of spinal posture data, such as simultaneous detection of sagittal and coronal curvature changes [122], but may reduce comfort and increase costs. Thus, sensor placement strategies should balance accuracy and practicality to maintain user comfort.

b. Gyroscopes. Gyroscopes measure angular velocity around the X, Y, and Z axes, detecting rotational motion and

TABLE IV
COMPARISON OF HIGH-CONTACT SENSORS COMMONLY USED IN HUMAN SITTING MONITORING SYSTEMS.

Sensor Type*		Product	Company	Price ($)	Measuring Range	Sensing Area (mm)	Accuracy	Studies
Motion	Accelerator	KXM52 3-Axis⋆	Kionix	-	± 2 g	-	± 2-3 %	[122]
	Accelerator	ADXL335^a	Analog Devices	5.53	± 3 g	-	-	[29]
	Gyroscope	ITG3200 3-Axis^b	InvenSense	-	±2000 °/s	-	±6 %	[128]
	IMU	MPU6050 6-Axis (Gyro + Accelerometer)^c	InvenSense	4.8	G: ±250-2000 dps A: ±2-16 g	-	-	[131], [134] [57]
	IMU	Next Generation IMU(NGIMU) 9-axis MEMs sensor^d	x-io Technologies	-	G: 2000 °/s A: 16 g M: 1300 uT	-	-	[55]
Deformation	FS	ZD10-100^e	Suzhou LEANSTAR Electronic	-	0-500 g	85×10	-	[132]
	FBG	Fiber Bragg Grating Array^f	AtGrating Technologies	-	-	10	-	[22], [126]

*The following notations are also used: "IMU" for inertial measurement units, "FS" for flex sensor, and "FBG" for fiber Bragg grating. In the "product" section, products marked with "⋆" indicate that the product is no longer in production.

^{a}https://www.analog.com/cn/products/adxl335.html

^{b}https://invensense.tdk.com/products/motion-tracking/3-axis/itg-3200/

^{c}https://invensense.tdk.com/products/motion-tracking/6-axis/mpu-6050/

^{d}https://x-io.co.uk/ngimu/

^{e}https://lssensor.cn/flexible-pressure-sensor/zd10-100.html

^{f}https://cn.atgrating.com/products/bare-fbg-array.html

directional changes. When an object rotates, the gyroscope senses torsional movements, converting them into electrical signals to calculate angular velocity. Gyroscopes are commonly used to monitor angular and directional changes in human posture, as demonstrated in gait tracking and lumbar spine motion analysis [128], [140], [141]. They are particularly effective for capturing dynamic posture transitions, complementing the static posture data obtained by accelerometers.

c. Inertial Measurement Units (IMU). IMUs combine accelerometers, gyroscopes [57], [124], [131], [134], and sometimes magnetometers [55], [129], into a single device, providing comprehensive motion and orientation data. Compared to individual sensors, IMUs offer superior motion-tracking capabilities but require more advanced data processing and are generally more expensive. Their integration of multiple sensing modalities makes them ideal for applications requiring high accuracy, though this comes at the cost of increased complexity and reduced affordability.

*2) **Deformation Sensors**:* Deformation sensors monitor sitting posture by detecting deformations such as bending or strain. Similar to motion sensors, deformation sensors are affordable, widely available, and typically integrated into garments. To ensure accuracy, these garments can be designed as stretchable compression clothing to accommodate users of different sizes, minimizing the impact of garment fit on measurement precision [142].

a. Flex Sensors (FS). FSs, previously discussed in the context of low-contact sensors, are also applied in high-contact scenarios. They are often attached to the back or neck to monitor real-time changes in curvature angles during posture adjustments [132]. FSs are lightweight, flexible, and suitable for long-term wear, making them practical for continuous posture monitoring.

b. Fiber Bragg Grating (FBG) Sensors. FBG sensors employ optical fiber gratings that reflect specific wavelengths of light, which shift under strain or deformation. These wavelength shifts are captured by a spectral analysis system to provide precise posture data [126]. A widely used example is a multiplexed FBG array sensor from AtGrating Technologies, designed specifically for spinal monitoring. This array includes seven gratings (λB: 1512–1559 nm), each encapsulated in a soft silicone substrate (Dragon Skin^{TM} 30) to conform to the physiological curvature of the back [126].

FBG systems excel in sensitivity and frequency response, outperforming inertial sensors in monitoring slow or subtle posture changes [143]–[145]. The multiplexed nature of these sensors allows for simultaneous monitoring of multiple body parts, offering comprehensive posture information. However, their cost and the complexity of spectral analysis systems may limit widespread adoption.

D. Sensor Configurations

In summary, posture monitoring systems utilize either single-modal or multi-modal sensors, each tailored to specific needs. Single-type systems [27], [49], [54], [56], [61], [65], [70], [91], [146] are widely used for their simplicity, cost-effectiveness, and ease of implementation. These systems rely on a single sensor type, making them ideal for basic posture monitoring tasks, with efficient data processing and real-time monitoring capabilities. However, their one-dimensional data limits accuracy in detecting complex posture changes and reduces adaptability in varied environments [18], [59].

To address these limitations, multi-modal sensor systems combine complementary technologies to enhance monitoring accuracy and data richness. Pressure sensors often serve as the foundation for two types of sensor systems, paired with technologies such as ultrasonic sensors [147]–[150], Microsoft Kinect [151], [152], or motion sensors like IMUs and accelerometers [98], [107], [153], [154]. Sparsely arranged FSRs are typically used to collect pressure distribution data from seated individuals. When combined with ultrasonic or infrared sensors, these systems enable precise distance measurements, improving spatial awareness in posture analysis. Similarly, integrating visual capture systems (such as cameras) with motion sensors (such as accelerometers or gyroscopes) allows simultaneous tracking of motion and visual cues, thereby enhancing the system's ability to detect posture changes and transitions [123], [155]. For more specialized monitoring, the combination of rigid LCs with inclinometers [156] or ECG dry electrodes [118] provides a comprehensive evaluation of posture's impact on spinal alignment and cardiac health. These setups are particularly valuable in clinical or experimental settings where detailed physiological data is required. Additionally, innovative approaches have integrated temperature and sound sensors [94], which infer posture indirectly by detecting changes in environmental and body temperature, as well as sound characteristics. This method offers a unique, non-intrusive perspective on posture monitoring where direct observation is not feasible.

Some studies have developed sitting posture monitoring systems using combinations of more than three sensor types. For example, integrating a six-axis gyroscope and accelerometer, an infrared proximity sensor, and FSRs [75], or combining accelerometers, magnetometers, altimeters, temperature sensors, FSRs, and temperature sensors [60], to maximize data diversity. Additionally, some research has developed more intelligent posture monitoring systems that incorporate sensors for vital signs and environmental parameters like heart rate, blood pressure, temperature, humidity, carbon dioxide, noise, and light [21], [157]. This approach can more comprehensively assess the impact of sitting on health. However, the integration of multi-modal sensors also causes increased system complexity, more challenges in data synchronization and processing, rising costs, and hardware integration difficulties.

III. Dataset Establishment

A. Participant Groups

The selection of participant groups is crucial for developing representative datasets in intelligent posture monitoring research. Variations in physiological and behavioral characteristics across populations result in diverse practical applications for posture data. To ensure dataset reliability, it is essential to define participant categories with an emphasis on diversity and inclusivity. Given the physiological and behavioral differences between the general population and individuals with mobility impairments, existing datasets are often categorized into two groups: healthy participants and wheelchair users. Ethical compliance is a core requirement, with all participants providing informed consent under protocols approved by relevant ethics committees. Participant groups are generally categorized into two main types: healthy individuals and wheelchair users, as summarized in Table V.

*1) **Healthy Participants**:* Healthy participants are individuals without musculoskeletal disorders, muscle injuries, or neurological diseases and who have not recently experienced back or neck pain [65], [117]. This group serves as the baseline for defining standard sitting posture patterns, such as "good" or "poor" posture. Their relatively stable postures make them ideal for developing classification and recognition algorithms in intelligent posture monitoring systems. As a result, healthy individuals are widely included in datasets for posture monitoring research [26], [27], [65], [91], [100], [117], [158].

To ensure dataset diversity and representativeness, factors such as age, gender, and occupational background should be considered. Physiological differences, such as those between men and women, as well as variations in height, weight, and BMI, can significantly influence posture behaviors [116]. Occupational factors are equally important; for example, office workers [65], students [27], and individuals who sit for over 8 hours daily [100] often exhibit distinct sitting patterns. Participant numbers typically range from several dozen [27], [91], [100], [158] to hundreds [65], depending on the study's objectives and available resources. Expanding sample sizes and ensuring demographic diversity are essential for creating reliable and broadly applicable datasets.

*2) **Wheelchair Users**:* Wheelchair users, including individuals with conditions such as stroke or hemiplegia, rely on wheelchairs for prolonged periods in their daily lives. Their limited mobility and extended sitting time often result in muscle and bone weakness, complicating trunk control [27]. Additionally, difficulty in adjusting posture increases the risk of pressure ulcers, particularly at bony prominences like the ischial tuberosities, calcaneus, and the back of the knees during prolonged sitting [28], [153], [160], [161]. Prolonged pressure restricts blood flow, reducing oxygen and nutrient supply to skin tissues and increasing the likelihood of deep tissue injury (DTI) [68], [162]. Poor sitting postures, such as leaning forward or to one side, further exacerbate risks by contributing to spinal deformities and breathing difficulties.

Research emphasizes that alleviating sustained pressure is the most effective strategy for preventing pressure ulcers [163]. An optimal sitting posture for wheelchair users should provide adequate spinal support and evenly distribute body pressure to minimize localized pressure and reduce ulcer risks [28]. Posture data collection from wheelchair users is critical for improving wheelchair designs and developing posture correction devices, such as specialized seat cushions.

While some studies simulate wheelchair postures using healthy participants in controlled settings [26]–[28], [159], this approach has inherent limitations. Long-term wheelchair users develop unique physiological adaptations, including altered pressure distribution, which cannot be replicated in short-term simulations. Therefore, direct data collection from wheelchair users, including those with progressive conditions

TABLE V
COMPARISON OF TWO MAIN CATEGORIES OF HEALTHY PARTICIPANTS AND WHEELCHAIR USERS.

Category	Physiological Structure	Sitting Behavior	Health Risks	Monitoring Objectives	Studies
Healthy participants	• Normal musculoskeletal structure • Natural spinal curve • Wide range of muscle activity	• Varied sitting habits • Frequent posture changes • Easy to adjust	• Poor sitting posture may lead to low back, neck and shoulder pain, etc	• Prevent health problems caused by poor sitting posture • Maintain good sitting habits	[65] [91] [100] [158]
Wheelchair users	• Possible muscle atrophy • Limited spinal curve • Restricted muscle activity	• Limited posture changes • Maintain a single posture for a long time • Limited ability to adjust posture	• Prolonged sitting may lead to pressure ulcers, muscle atrophy, scoliosis, etc	• Prevent pressure ulcers and scoliosis • Maintain spinal stability • Improve long-term sitting comfort	[27] [29] [159]

like multiple sclerosis [29], is essential for achieving accurate and representative results. Simulated experiments, however, can complement preliminary research, providing additional support for the reliability and applicability of findings [27].

B. Posture Categories

Classifying sitting postures is critical for accurate monitoring and assessment in intelligent sitting monitoring systems, as different postures directly impact spinal alignment, muscle engagement, and overall health. These systems aim to identify and distinguish postures in real time, providing alerts or recommendations when deviations occur. This functionality supports the timely correction of poor postures and helps prevent posture-related health issues.

Postures are generally classified as “healthy” or “poor”. According to the International Ergonomics Association, a standard healthy sitting posture includes: (1) thighs and lower legs forming an angle close to or greater than 90 degrees, (2) feet flat on the ground, (3) a slightly reclined torso with a straight-ahead gaze, and (4) lumbar support to maintain the natural spinal curvature [164]. Improper postures increase musculoskeletal strain [164], and prolonged sitting in any position may lead to discomfort or pain [165], [166]. Notably, there is no conclusive evidence that any single posture offers superior health benefits, highlighting the need for adaptable and personalized monitoring strategies [164].

A review of the literature identified 37 distinct sitting postures detected by intelligent monitoring systems [18], [21], [27], [49], [51], [56], [60], [61], [65], [79], [100], [110], [114], making it the most comprehensive categorization to date, as shown in Fig. 5. A detailed description of these postures is provided later in this section. These postures include full-body positions from both front and side views, while detailed upper-body positions are covered in other studies [20], [55], [59], [63], [70], [167]. Postures involve complex combinations of torso, head, upper limb, and lower limb states [59], [168]. Torso positions include upright, forward-leaning, backward-leaning, lateral tilt, and rotation. Head positions are categorized as upright or non-upright (e.g., axial rotation or lateral flexion). Upper limbs may rest on a table, armrests, or support the chin, while lower limb positions include flat feet, extended legs, crossed legs, crossed ankles, or one leg raised.

Among the 37 postures presented in Fig. 5, commonly recommended sitting postures are (1) sitting upright and (5) leaning backward [18], [59]. Posture (1) features an upright torso with the pelvis fully seated and feet flat on the ground. Posture (5) involves leaning on the seatback, with the pelvis fully seated and the back straight. These are considered low-risk postures as they impose minimal stress on the body [18], [59]. In contrast, other postures, such as leaning forward, hunching, or crossing legs, are associated with a higher risk of lower back pain and work-related musculoskeletal disorders (WMSDs) [18]. Ergonomic assessment is essential for monitoring these postures, enabling the development of interventions to mitigate the adverse effects of prolonged sitting.

The most frequently monitored postures in research include (1) sitting upright, (3) leaning forward, (4) hunchback, (5) leaning backward, (19) leaning left, (20) leaning right, (23) left leg crossed over right, and (24) right leg crossed over left. Detailed analyses of these postures provide insights into their effects on musculoskeletal health and inform ergonomic improvements [18], [105], [110], [169].

C. Chair Types

As the primary interface between the human body and its environment, the design and functionality of a chair play a pivotal role in determining sitting posture, muscle load distribution, and overall comfort. Thus, the choice of chair is a critical consideration in sitting posture monitoring studies. Chairs used in experiments are generally categorized into two main types: office chairs and wheelchairs.

*1) **Office Chairs**:* Office chairs are commonly used in sitting posture studies, though specific models are often unspecified. Simple chairs without armrests [16], [51], [59], [170], [171] provide minimal back support, requiring users to rely on muscle strength for posture maintenance. In contrast, chairs with armrests [9], [49], [50], [53], [91], [158] offer additional support for the upper limbs and back, promoting greater stability. Ergonomic office chairs with adjustable features, such

Fig. 5. The most comprehensive summary of sitting posture categories monitored by intelligent systems. The categories were defined based on two views, the front view and the side view. Upright sitting was used as the standard posture. (1-1) represents the sitting upright side view, and (1-2) represents the sitting upright front view. (2)-(18) show variations of each sitting posture compared to the side view of the upright sitting posture. (19)-(37) show variation of each sitting posture compared to the front view of the upright sitting posture. (2) Sitting upright at the front edge, (3) leaning forward, (4) hunchback, (5) leaning backward, (6) left leg forward, (7) right leg forward, (8) legs forward, (9) ankles crossed, left foot up, (10) ankles crossed, right foot up, (11) leaning forward at the front edge, (12) hunchback at the front edge, (13) leaning back with hips slightly forward, (14) leaning back with left leg forward, (15) leaning back with right leg forward, (16) leaning back with legs forward, (17) ankles crossed, left foot up, legs forward, (18) ankles crossed, right foot up, legs forward, (19) leaning left, (20) leaning right, (21) torso left, (22) torso right, (23) left leg crossed over right, (24) right leg crossed over left, (25) left leg crossed, (26) right leg crossed, (27) leaning left with left arm support, (28) leaning right with right arm support, (29) left leg over right, leaning left, (30) left leg over right, leaning right, (31) right leg over left, leaning left, (32) right leg over left, leaning right, (33) left leg crossed, leaning right, (34) right leg crossed, leaning left, (35) left leg raised, (36) right leg raised, (37) legs crossed.

as height, tilt, and armrests [100], are frequently employed in simulated office settings to replicate real-world scenarios.

The seat surface also influences pressure distribution and posture stability. Rigid surfaces are ideal for pressure data collection, particularly with sensors like FSRs, as they enhance sensitivity to pressure variations. However, prolonged use of rigid surfaces may lead to discomfort, encouraging frequent posture adjustments. To address this, some studies use foam padding or softer seat surfaces [21], [107], balancing comfort with sensitivity. While softer surfaces improve user comfort, they may reduce the system's ability to detect minor posture changes.

*2) **Wheelchairs**:* Wheelchairs are essential assistive devices for approximately 75 million people worldwide who experience mobility impairments [27]. They are widely used in studies on sitting postures of individuals with conditions such as stroke or spinal injuries [26]–[28]. Wheelchairs are typically equipped with specialized features, including back supports, cushions, and leg supports, to enhance user comfort and stability.

Most research involving wheelchair users does not specify the types of wheelchairs used, highlighting a gap in understanding how different designs influence posture. Studies commonly utilize manual wheelchairs [28], but further research is needed to explore the impact of variations in wheelchair design on sitting postures and pressure distribution.

IV. Model Construction

The construction pipeline of the AI model designed for sitting posture classification comprises four primary phases: (1) data preprocessing, (2) feature extraction, (3) posture classification, and (4) performance evaluation, as depicted in Fig. 6. As detailed in Chapter II on data capture, the acquired data can be broadly categorized into three main types: (1) body images, (2) pressure arrays, and (3) electrical signals. These data undergo distinct preprocessing and feature extraction methods to derive relevant features, subsequently fed into diverse classifiers for posture classification.

A. Data Preprocessing and Feature Extraction

In this pipeline, data preprocessing cleans, normalizes, and integrates raw data from body images, pressure arrays, and electrical signals for quality and compatibility. Feature extraction then selects and transforms key information from the preprocessed data to create a concise representation vital for distinguishing postures, enhancing model performance by reducing complexity and boosting classification accuracy, guiding classifiers for effective posture classification.

*1) **Body Images**:* Body images utilized for sitting posture detection are usually captured by using non-contact Sensors (See Section II-A). They typically encompass RGB images [35], [69], [167], [172], [176], [180], [181], RGB-D images [70], [176], [179], and thermal images [20], [59].

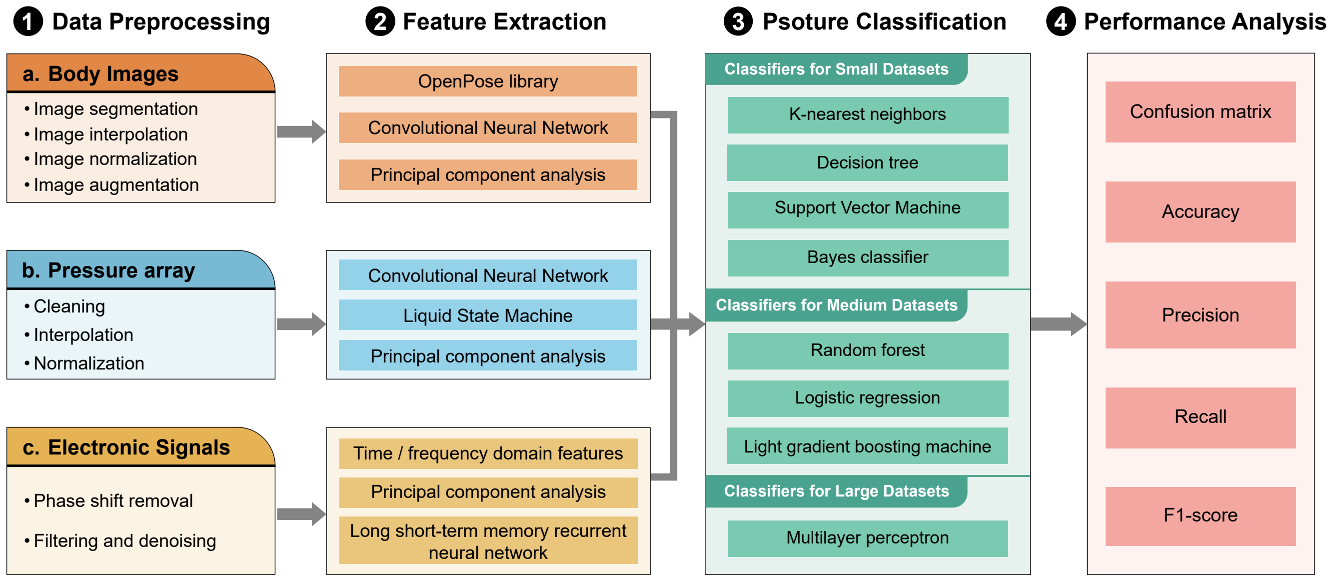

Fig. 6. Summarized pipeline of the classification model construction for an intelligent posture monitoring system. The process consists 4 steps: (1) data preprocessing, involving cleaning, normalization and integration techniques for raw data from body images [20], [59], [69], [172], pressure arrays [51], [65], [150], [173], and electrical signals [49], [120], [170], [174], (2) feature extraction [67], [86], [175], [176], where key information from the preprocessed data is selected and transformed to create a concise representation vital for distinguishing postures, (3) posture classification, which categorizes data into posture types using classifiers suited for small [51], [150], [174], [177], medium [56], [65], [120], [177] and large [67], [86], [109], [178] datasets, (4) performance analysis, assessing the classification performance through key metrics like confusion matrix, accuracy, precision, recall, and F1-score [27], [56], [70], [179].

a. Data Preprocessing. Data preprocessing is a vital stage in sitting image analysis, involving various techniques such as segmentation [69], interpolation [20], normalization [59], and augmentation [59], [172]. When handling RGB images, optimizing preprocessing steps for prompt response times often includes body segmentation to differentiate the human body from the background environment [69]. And in the preprocessing stage for deep learning model deployment, the Torch2TRT tool is utilized to convert the PyTorch-trained ResNet18 model into a TensorRT-compatible format and optimize the data precision to FP16 (16-bit floating point), thereby enhancing the model's computational efficiency for real-time inference [182]. For thermal images, normalizing the data is crucial to converting raw data from each frame into a standardized range of 0 to 1 [59]. Additionally, the utilization of interpolation techniques [20], is instrumental in enhancing the resolution of low-resolution thermal images. Furthermore, image augmentation is a widely adopted practice to enrich training datasets, involving techniques such as rotation, translation, and scaling, particularly beneficial for body images [59], [172].

b. Feature Extraction. In recent studies, convolutional neural networks have emerged as the primary method for feature extraction in sitting images. For RGB images, the OpenPose library[1] [175] is extensively employed for detecting key body points, which serve as crucial image features [167], [176], [180]. Beyond keypoint detection methods, end-to-end deep learning architectures have been applied for sitting posture feature representation. For instance, ResNet18 extracts human skeletal features from RGB video images [182], and a multi-scale spatiotemporal graph convolutional network (M2SGCN) with a recurrent neural network module learns hierarchical spatiotemporal features from skeletal keypoints and angles [183]. To address model complexity, the Light Convolution Core (LCC) with Tied Block Convolution (TBC) and Convolutional Block Attention Module (CBAM) are adopted to reduce parameters for multi-person sitting posture analysis [184]. Additionally, another research employs a deep fusion architecture that integrates VGG13 for shallow feature extraction, ResNet18 with residual blocks for multidimensional feature extraction, and Vision Transformer with multi-head self-attention for global context to learn hierarchical representations from RGB images [185]. When dealing with a sitting posture problem RGB-D images, techniques such as depthwise convolutional blocks [186] and MobileNetV2[2] [187], are utilized to capture features from RGB-D frame sequences effectively. For thermal images, Principal Component Analysis (PCA) methods are leveraged to select discriminative features and enhance classifier recognition performance [20]. Additionally, residual networks [188], as demonstrated in prior research [59], are employed for feature extraction in thermal imagery analysis. Furthermore, residual networks integrated with cross-modal self-attention modules are applied to realize cross-modal feature fusion of thermal and pressure map data in posture recognition [189].

*2) **Pressure Array:*** Low-contact sensors, as classified in Section II-B, delineate pressure arrays into two distinct types: sparse pressure arrays, captured by sparsely distributed pres-

[1]https://github.com/CMU-Perceptual-Computing-Lab/openpose

[2]https://github.com/pytorch/vision/blob/main/torchvision/models

sure sensors, and dense pressure arrays, captured by densely distributed pressure sensors. Each category demands tailored data preprocessing and feature extraction techniques to account for their unique characteristics.

a. Data Preprocessing. The preparation of pressure array data entails a series of essential steps encompassing cleaning, interpolation, and normalization procedures. In the context of sparse pressure arrays, the data cleaning phase typically addresses the elimination of redundant, corrupted, and null entries within the dataset [65], [150], [173].

To further optimize data efficiency, adaptive compressed sensing techniques such as adaptive stepsize forward–backward pursuit (ASFBP) [190] can be applied to compress raw signals below the Nyquist rate, reducing dimensionality while maintaining feature integrity. Furthermore, the sparse pressure array may undergo a transformation into a dense format via the application of the image bicubic interpolation method [147], [191]. In scenarios involving dense or sparse pressure arrays, normalization serves as a pivotal technique to standardize the raw data from individual frames into a consistent range [27], [51], [53], [65], [91], [158].

b. Feature Extraction. When dealing with dense pressure arrays represented as 2D matrices, feature extraction commonly relies on convolutional neural networks (CNNs), such as the VGG19 pre-trained model [147], Liquid State Machine [89], and various other CNN architectures [86], [109], [178]. Additionally, classic image feature extraction methodologies find application in dense pressure arrays, including the gray-level co-occurrence matrix (GLCM) [178] and principal component analysis (PCA) [178], [192]. Conversely, for sparse pressure arrays, the preprocessed data can be reshaped into a vector format, serving as input features for subsequent classification tasks [173]. In a recent study [193], an sparse pressure array was transformed into a time steps $\times$ features vector and fed into deep learning models, such as Echo Memory Network (EMN) and LSTM, enabling automatic extraction of temporal-spatial features from sequential pressure signals. Moreover, it is confirmed that the deep learning model performs better than the traditional methods in solving the fuzzy sitting posture classification problem.

TABLE VI
SUMMARY OF MODEL CONSTRUCTION PIPELINE.

Stage	Data Type	Key Methods	Studies
Data Preprocessing	Body images	Image segmentation	[69]
		Image interpolation	[20]
		Image normalization	[59]
		Image augmentation	[59], [172]
	Pressure array	Cleaning	[150], [173]
		Interpolation	[147], [191]
		Normalization	[27], [51], [53], [65]
	Electronic signals	Phase shift removal	[120], [170]
		Filtering and denoising	[49], [170], [174]
Feature Extraction	Body images	OpenPose library	[167], [175], [176]
		CNN	[186], [187]
		PCA	[20]
	Pressure array	CNN	[86], [89], [178]
		Liquid State Machine	[89]
		PCA	[178], [192]
	Electronic signals	TD / FD features	[120], [170]
		PCA	[67], [170]
		LSTM-RNN	[55]
Classifier Construction	Small datasets	KNN	[49], [51], [65] [150], [173], [174]
		Decision tree	[49], [51], [65] [177], [194]
		SVM	[49], [91], [158] [177], [178], [194]
		Bayes classifier	[22], [49], [150]
	Medium datasets	Random forest	[49], [51], [56] [65], [120], [177]
		Logistic regression	[51], [55], [89] [150], [172]
		LightGBM	[177], [194]
	Large datasets	MLP	[27], [53], [67] [86], [170], [178]
Classifier Evaluation	General metrics	Confusion matrix accuracy, precision recall, F1-score	[27], [51], [56] [70], [179]

*The following notations are also used: "CNN" for Convolutional Neural Network, "PCA" for Principal Component Analysis, "TD / FD" for Time Domain / Frequency Domain, "LSTM-RNN" for Long Short-Term Memory Recurrent Neural Network, "KNN" for k-Nearest Neighbors, "SVM" for Support Vector Machine, "LightGBM" for Light Gradient-Boosting Machine, and "MLP" for Multilayer Perceptron.

*3) **Electronic Signals**:* The high-contact sensors, as detailed in Section II-C, typically generate electronic signals that can be interpreted as time series data. In practical scenarios, a system comprising multiple high-contact sensors necessitates the simultaneous processing of their respective time series data, followed by integration for posture classification purposes.

a. Data Preprocessing. Data preprocessing of electronic signals involves a critical sequence of operations essential for enhancing signal quality and preparing it for subsequent analysis. This process typically includes phase shift removal, signal filtering, and denoising. Phase shift removal is a crucial step aimed at rectifying disparities between peak and valley values within the raw data, which is essential for mitigating hardware-related variations that may affect signal accuracy [120], [170]. Data filtering and denoising techniques are employed to reduce noise interference in the signal. This involves applying methods such as mean filtering [49], low-pass filtering [174], and utilizing wavelet denoising filters to enhance signal clarity and fidelity [120], [170].

b. Feature Extraction. In the realm of posture classification, the extraction of features from both the time and frequency domains holds significant importance for comprehensive signal analysis [120], [170]. Parameters such as mean, range, variance, standard deviation, energy, and entropy are pivotal in capturing the essential characteristics of the signal. Principal Component Analysis (PCA) emerges as a valuable tool for dimensionality reduction and identifying the most informative features that collectively contribute to over 95% of the variance in the data [67], [170]. Moreover, the utilization of Long Short-Term Memory (LSTM)-based Recurrent Neural Networks (RNNs) is instrumental in leveraging temporal dependencies within the data, thereby enhancing information extraction and aiding in more accurate posture recognition tasks [55].

B. Classifier Construction

Sitting posture classifiers are essential for uncovering patterns within training data and generalizing them to unseen datasets. Furthermore, the grid search method is widely used to find optimal parameters for the classifier [178]. The selection of a classifier[3] is contingent upon the size and intricacy of the dataset.

- K-nearest neighbor (KNN), decision trees, support vector machines (SVM), and Bayes classifiers are recognized for their efficiency with relatively small datasets, typically ranging from a few dozen to a few hundred samples per class.
- Random forests, logistic regression, and Light gradient boosting machine (LightGBM) prove effective with medium-sized datasets, which typically range from a few hundred to a few thousand samples per class.
- Multilayer Perceptron (MLP) networks excel in managing large datasets, which may contain thousands to millions of samples per class. Their capacity to grasp intricate patterns and relationships within the data makes them suitable for such extensive datasets.

*1) **Classifiers for Small Datasets:*** **a. KNN.** The KNN classifier operates by creating a multidimensional feature space, where it is assumed that data points within the same class share similar characteristics and are clustered closely together. After training the classifier and establishing the feature space, the class of a new data point is determined by examining the classes of its K-nearest neighbors. The class with the majority among these neighbors is the one assigned to the new point. Previous studies [18], [49], [51], [65], [150], [173], [174], [177], [194], [195] leverage the characteristics of the KNN model by positioning numerous sitting posture coordinates within a multidimensional space.

b. Decision Tree. A decision tree is a flowchart-like structure designed for making decisions or predictions. It comprises nodes that represent decisions or tests on attributes, branches that indicate the outcomes of these decisions, and leaf nodes that signify final outcomes or predictions. Each internal node corresponds to a test on an attribute, each branch reflects the result of that test, and each leaf node represents a class label or a continuous value. Metrics for splitting the data include Gini impurity, entropy, or information gain. Previous studies [49], [51], [51], [65], [177], [194] calculate the Gini coefficients for different sitting postures to perform sitting posture division.

c. SVM. SVMs achieve non-linear classification through the kernel trick, which represents the data using a set of pairwise similarity comparisons between original data points via a kernel function. This function transforms the data into coordinates in a higher-dimensional feature space. Consequently, SVMs utilize the kernel trick (e.g., Radial Based Function (RBF) kernel) to implicitly map their inputs into these high-dimensional spaces, allowing for linear classification to be effectively performed [49], [51], [65], [91], [158], [177], [178], [194].

d. Bayes Classifier. Bayes classifier is characterized by using Bayes Theorem to calculate probabilities, which is the classifier having the smallest probability of misclassification of all classifiers using the same set of features. Previous studies [22], [49], [49], [65], [150] implement a Naive Bayes classifier to assess the wearable system's ability to recognize the upright, kyphotic, and lordotic sitting postures assumed by the participants.

*2) **Classifiers for Medium Datasets:*** **a. Random Forest.** Random forest is a variant of decision trees used to enhance performance beyond that of a single tree. Each decision tree in the forest makes its own classification and generates a result. The forest then determines the final prediction by selecting the most frequently occurring outcome. While the Bootstrap method helps reduce overfitting, it can make result interpretation more complex due to the presence of multiple decision trees. Previous studies [49], [51], [56], [65], [120], [177] chose the random forest classifier because it can achieve high performance without complicated parameter adjusting.

b. Logistic Regression. Logistic regression predicts the likelihood that a data point falls into one of two mutually exclusive categories. In the context of posture analysis, it determines whether a point corresponds to a specific posture. Previous studies [51], [51], [55], [65], [89], [150], [172] use Sigmoid as the activation function of the classifier in their temporal posture discrimination module, generating K binary classifiers. When predicting, the sitting posture data will be put into the K classifiers, and the classifier with the highest prediction score wins.

c. LightGBM. LightGBM, utilizing gradient boosting and histogram-based techniques, stands out for its vertical tree topology, contrary to traditional horizontal approaches. By growing trees leaf-wise, it minimizes loss effectively and operates efficiently with medium and large-sized datasets while prioritizing result accuracy for sitting postures [177], [194]. However, overfitting risks persist with smaller datasets, a common trait among decision tree algorithms. LightGBM simplifies the complex task of identifying optimal split points, enhancing its overall performance.

*3) **Classifiers for Large Datasets:*** Multilayer Perceptron (MLP) networks, are multilayer artificial neural networks, which are supervised learning methods that use the back-propagation algorithm for training. They are based on the gradient descent method that seeks to modify the weights of each neuron to reduce the global error, starting from the last layer and continuing with the preceding layers. They usually integrate with the CNN-based feature extraction model to classify sitting postures [27], [53], [65], [67], [86], [91], [96], [109], [170], [178]. In a specific study, Bi et al. [67] utilize MLP in conjunction with a Generative Adversarial Network (GAN) to enhance the accuracy of sitting posture recognition.

C. Classifier Evaluation

Key metrics are pivotal for assessing classifier performance, including confusion matrix, accuracy, precision, recall, and F1-score [4].

[3] https://scikit-learn.org/dev/auto_examples/classification/

[4] https://scikit-learn.org/dev/modules/model_evaluation.html

*1) **Confusion matrix**:* A confusion matrix is a widely used table that summarizes the classification results of a classifier [27], [56], [70], [179]. It offers a detailed analysis of a model's performance by displaying the counts of true positives (TP), true negatives (TN), false positives (FP), and false negatives (FN).

*2) **Accuracy**:* Accuracy measures the proportion of correct predictions made by the model out of all the predictions. A high accuracy score indicates that the model is making a large proportion of correct predictions, while a low accuracy score indicates that the model is making too many incorrect predictions. Accuracy is calculated using the following form:

$$acc. = \frac{TP + TN}{TP + TN + FP + FN} \tag{1}$$

*3) **Precision**:* Precision is a metric that measures the accuracy of the positive predictions made by the model. A high precision score indicates that the model is able to accurately identify positive instances, while a low precision score indicates that the model is making too many false positive (FP) predictions. Precision is calculated using the following form:

$$prec. = \frac{TP}{TP + FP} \tag{2}$$

*4) **Recall**:* Recall, also known as sensitivity or true positive rate (TPR), measures the model's ability to correctly identify positive instances. A high recall score indicates that the model is able to identify a large proportion of positive instances, while a low recall score indicates that the model is missing many positive instances. Recall is calculated using the following form:

$$recall = \frac{TP}{TP + FN} \tag{3}$$

*5) **F1-score**:* The F1-score is a performance metric that combines precision and recall to provide a comprehensive evaluation of a binary classification model. It calculates the harmonic mean of precision and recall, treating both metrics with equal importance. A high F1-score indicates strong performance in both precision and recall, while a low F1-score suggests poor performance in either or both metrics. F1-score is calculated using the following form:

$$f1 = \frac{2 * prec. * recall}{(prec. + recall)} \tag{4}$$

V. System Feedback

System feedback plays a pivotal role in communicating posture monitoring results to users. Once data is collected via sensors, it is processed using algorithms and classification techniques to detect and evaluate sitting postures. By providing continuous feedback, these systems raise user awareness of poor postures, encourage proactive adjustments, and promote healthier spinal habits [156]. This process not only helps users develop better sitting habits but also supports broader health management objectives.

Sitting monitoring systems typically deliver feedback through three primary modalities: visual, tactile, and auditory, as summarized in Table VII.

A. Visual Feedback

Visual feedback is a common and effective modality in intelligent sitting posture monitoring systems, presenting posture data in easily interpretable formats. It can be classified into digital visual feedback and physical visual feedback.

Digital visual feedback uses virtual formats such as mobile applications or web interfaces to present posture data through charts, text, images, and digital avatars. Common chart types include line graphs [57], [157], [199], bar charts [146], [200], [201], pie charts [147], [201], [202], dials [203], [204], heat maps [16], [147], [205], [206], amoeba-like blob charts [207], and scatter plots [208], which visually represent posture trends and statistical information. Text feedback provides concise posture reminders, such as daily email summaries [156] or prompts to adjust posture, take breaks, or exercise [85], [201], [209], [210]. Image feedback includes real-time photos [211], schematic posture diagrams [64], [152], [156], [200], [202], [212], virtual skeletons [213], and real-time videos [214], [215], helping users visualize the difference between their current and ideal postures. Digital avatars [216]–[220] offer an intuitive representation of the user's posture and are often combined with gamified feedback mechanisms, such as badges [216], score rankings [152], or virtual plant growth [134]. These features make digital feedback highly flexible, accessible across mobile devices and computers, and effective for presenting complex information.

Physical visual feedback uses physical devices such as LED lights or physical avatars to directly display posture information. LED lights indicate posture status through color changes or blinking frequencies (e.g., green for correct posture, red for adjustments needed). These lights are integrated into chairs [221], clothing [222], [223], or placed near computer displays [148], [219]. Physical avatars, like flowers [75], origami structures [224], or interactive agents [225], change shape or behavior based on the user's posture. Additional interventions include dimming computer displays [48] or flashing screens on devices [199], [226], [227], drawing immediate attention to poor posture.

Visual feedback improves user engagement by offering real-time prompts for immediate corrections and summarizing long-term posture trends through charts or reports. By comparing current postures with ideal or historical data, users can identify posture issues and track progress effectively, promoting sustained improvements in sitting habits.

B. Tactile Feedback

Tactile feedback uses physical sensations, such as vibrations, air pulses, or mechanical movements, to alert users to improper posture [130], [148], [198]. Common implementations include vibrators embedded in chairs that activate when posture deviations are detected [112], [117], [196], [212], and pneumatic systems that deliver air pulses through bladders for localized feedback [205], [228], [229]. Advanced methods, such as electrical muscle stimulation (EMS), trigger targeted muscle contractions to encourage posture correction [209]. Some chairs also actively adjust seat angles to improve posture [230]. Other systems incorporate tactile elements, like wooden

TABLE VII
COMPARISON OF SYSTEM FEEDBACK MODALITIES IN SITTING POSTURE MONITORING SYSTEMS.

Feedback Type	Form of Presentation	Advantages	Disadvantages	Studies
Visual Feedback	• Digital forms: charts, text, images, digital avatars • Physical objects: LED, physical avatars	• Provides detailed and clear information • Allows users to review and analyze data	• Requires active user engagement • Less effective in highly visual task environments	[26], [51] [53], [54]
Tactile Feedback	• Vibration • Air pulses • Physical contact or mechanical movement	• Immediate feedback without interrupting visual or auditory tasks	• Limited information capacity • Usually only prompt posture adjustments • High cost for physical or mechanical feedback	[65], [89] [117], [196]
Auditory Feedback	• Voice prompts • Short buzzer alert	• Instant notifications • Suitable for multitasking environments	• May disrupt quiet settings • Frequent alerts can be annoying	[21], [62] [197], [198]

beads for back stimulation [227], or actuators in keyboards, mice, and monitors that move or rotate to prompt adjustments [231].

Tactile feedback provides localized or full-body stimulation, offering an immediate and effective means of correcting posture through physical contact. This approach is particularly useful in office environments where visual or auditory feedback might be ignored, delivering timely reminders to maintain proper posture. However, tactile feedback lacks the ability to guide users in selecting the correct posture, making it less instructive compared to visual feedback.

C. Auditory Feedback

Auditory feedback uses sound or voice cues to prompt users to adjust their posture. This method includes verbal instructions or warnings [197], [209], [225], [232], [233] and short buzzer alerts [57], [62], [76], [155], [225]. Its immediacy and effectiveness make it an efficient way to capture users' attention and encourage posture adjustments. However, careful volume control is essential to avoid disturbing others or compromising user privacy.

D. Evaluation of System Feedback

Evaluating system feedback is essential to ensure posture monitoring systems meet user needs and effectively improve posture habits. Currently, most studies on the effectiveness of posture monitoring feedback evaluate sitting posture by recruiting participants to perform specific tasks for predetermined durations [78], [201], [209]. Key evaluation metrics include accuracy, timeliness, user acceptance, and impact on posture improvement. While accuracy testing is widely conducted, relatively few studies [27], [51], [96], [209] focus on usability or user experience. Research indicates that feedback can enhance posture correction and user comfort [48], [96], [146], [196], [234]–[238], particularly when integrating multi-sensory feedback such as visual, tactile, and auditory modalities [65], [117], [129].

However, findings on the effectiveness of multisensory integration feedback compared to single-modal approaches are inconsistent. Some studies [197], [201], [239], [240] demonstrate the advantages of multisensory integration, while others report no significant improvement [146], [212]. Regarding single-modal feedback comparisons, studies show tactile feedback yields significantly faster postural correction response times than visual [209], [241] and auditory feedback [209]. This advantage is task-dependent, with tactile feedback achieving 54% and 39% faster response times in high-load tasks (mobile gaming, $p<0.01$), while the advantage diminishes in low-load scenarios (text entry) [209]. For forward head posture, tactile (15.8 mm) and auditory (16.3 mm) reduce anterior displacement comparably, though tactile receives higher appropriateness ratings [78]. User perception shows 100% noticeability for tactile compared to 58% for visual [227], with higher accuracy ratings [209]. Notably, 71% of users prefer visual cues in public due to auditory feedback's noise sensitivity [201]. The lack of standardized evaluation protocols limits comparability across studies and scalability of feedback systems. Future research should focus on developing multidimensional, context-specific evaluation frameworks to refine feedback modalities and enhance usability.

Furthermore, the impact of efficacy disparities across multisensory feedback modalities on data collection remains unexplored. Critically, extant literature identifies feedback acceptance barriers as a fundamental constraint. Tactile feedback's high intrusiveness risks premature abandonment and incomplete data collection [241], whereas visual/auditory modalities suffer neglect in demanding contexts, causing partial data omission and context-dependent validity constraints [201], [209]. This research gap necessitates rigorous investigation into how cross-modal efficacy variations influence data acquisition integrity.

VI. DISCUSSIONS

A. Limitations

This section consolidates the key limitations identified across four critical phases: data capture, dataset establishment, model construction, and system feedback.

*1) **Data Capture**:* Sensor-based intelligent posture monitoring systems face challenges in accuracy, stability, comfort, and adaptability. Pressure and wearable motion sensors require regular calibration to maintain precision, as prolonged use can result in drift and reduced reliability [16], [27], [45], [115], [122], [124], [171]. High-contact sensors, while effective, often compromise user comfort, making them less practical for extended use [49], [59], [120]. Non-contact sensors, such as camera-based systems, raise privacy concerns, particularly in sensitive environments [110], [116], [120], [170]. Achieving a balance between comfort, accuracy, and privacy remains a significant design challenge.

Cost and complexity are also critical considerations. Sparsely distributed pressure sensors offer a cost-effective alternative to large-area sensors but require further research to optimize placement strategies. Furthermore, the focus on single-type sensors limits the ability to capture complex postures involving the head, torso, and limbs under varied conditions [27], [49], [54], [56], [59], [61], [65], [70], [91], [146]. Multi-sensor integration has the potential to improve classification accuracy and system robustness [18], but it introduces technical challenges related to data fusion and processing.

Beyond these, limitations exist in real-time performance evaluation and sensor response characterization. The field lacks standardized real-time performance evaluation criteria. Fragmented metrics, including sampling frequency (or interval) of the data acquisition device [17], [18], [22], [27], [87], [242], average single-sample processing time (or processed samples/sec) [182], [183], and overall system latency [86], [184], hinder cross-system comparisons. For sensor response, current research is insufficient: limited studies report sensor response time metrics, and measurement protocols are inconsistent [86], [243]. This lack of reporting and standardization impedes systematic analysis of sensor performance differences, critical for optimizing data capture quality.

*2) **Dataset Establishment**:* The quality and diversity of datasets significantly impact model training and validation. Many studies rely on small sample sizes with limited demographic diversity, focusing primarily on healthy participants while neglecting wheelchair users and individuals with musculoskeletal disorders. Data collection across different chair types is also underexplored, restricting the adaptability of posture monitoring systems to varied environments [116]. Moreover, publicly available datasets are scarce, limiting opportunities for cross-study validation and broader application. For instance, Luna et al. [5] provide one of the few open-access datasets, comprising data from 12 participants using six FSR sensors across seven postures.

*3) **Model Construction**:* Classifier models often rely on data from fewer than 25 subjects [9], [49], [53], [59], [89], [91], [110], [127], [158], raising concerns about their generalizability. Furthermore, current models typically detect fewer than 12 postures, despite literature documenting 37 distinct sitting postures [16], [27], [54], [55], [59], [65], [91], [110], [158]. These models also struggle to capture subtle variations in spinal alignment, a critical factor for health outcomes. The lack of AI models capable of 3D posture prediction and analysis further limits their applicability [244], [245]. Addressing these gaps is crucial for advancing the functionality and relevance of posture monitoring systems.

*4) **System Feedback**:* Few studies evaluate the effectiveness of feedback modalities through user research or experimental comparisons [27], [51], [96]. Most research prioritizes posture classification accuracy while neglecting the design and usability of feedback systems [9], [50], [91], [158], [171]. The absence of standardized metrics for evaluating posture improvement yields heterogeneous findings, hindering cross-study comparability and impeding generalizable conclusions about feedback modality effectiveness. There is insufficient focus on user satisfaction and the impact of feedback on posture improvement. While some systems incorporate feedback mechanisms, their effectiveness and user experience remain underexplored. Moreover, in-depth research investigating the link between multisensory feedback efficacy disparities and data collection remains lacking. Future research should prioritize developing and evaluating feedback modalities to enhance usability and effectiveness in real-world applications.

B. Future Work

Future advancements in intelligent sitting posture monitoring systems will focus on intelligent feedback mechanisms, personalized health management, and expanded applications. The integration of Internet of Things (IoT) technology [53], [68], [116], [120], [242], [246], [247] will enable remote health monitoring and real-time feedback, though privacy-preserving edge computing and federated learning should be prioritized to minimize raw data transmission. Leveraging 5G and cloud computing, posture data can be transmitted instantly to medical institutions or home care platforms, facilitating cross-regional health management. This will improve user convenience by offering timely posture correction suggestions, reducing the risk of health issues caused by prolonged sitting and poor posture.

Personalized adjustments and health management are critical areas for future research. Although intelligent monitoring systems are commonly used in office settings, further studies should target specific populations such as the elderly, drivers, and individuals with medical conditions. For example, systems designed for wheelchair users should provide not only long-term posture monitoring but also personalized adjustment recommendations to prevent pressure ulcers and related health issues [29]. Building large-scale, diverse posture datasets will be essential for tailoring feedback to individual body characteristics and sitting habits.

The integration of multi-modal sensors will significantly enhance system capabilities, allowing for comprehensive health monitoring. Prior research has explored combining heart rate monitors and other sensors to provide multidimensional health assessments [60], [96], [118], [157]. Future efforts should optimize data fusion techniques to improve the accuracy and robustness of these systems. Additionally, algorithms must be

[5] https://www.mdpi.com/article/10 .3390/electronics10151825/s1

developed to handle data noise effectively, ensuring reliable posture recognition in varied environments. Sensor design improvements should focus on balancing accuracy, stability, comfort, and privacy protection.

User-centered design will remain crucial for system optimization. Conducting usability testing and user interviews [27], [51], [96] will provide valuable insights into user satisfaction, enabling iterative refinements to improve user experience and long-term adoption. Systems must prioritize ease of use and adaptability to different environments, while also integrating standardized regulatory frameworks for public and office sensor data workflows.

Incorporating virtual reality (VR) and augmented reality (AR) technologies offers exciting possibilities for enhanced interaction. These technologies could provide immersive, real-time posture guidance, helping users visualize and adjust their posture more effectively [248]. Such innovations will further enhance the functionality and user engagement of intelligent posture monitoring systems.

VII. Conclusion

This survey has explored the state-of-the-art in intelligent sitting posture monitoring systems, focusing on key phases including data capture, dataset establishment, model construction, and system feedback. While advancements in sensor technology and machine learning have enhanced posture monitoring capabilities, challenges remain in achieving sensor accuracy, user comfort, and privacy protection, which limit widespread adoption. Current datasets often lack diversity, and classification models struggle to generalize to complex postures and new users. Furthermore, feedback mechanisms frequently overlook user experience and long-term usability.

Future research can focus on integrating diverse sensor types to improve posture recognition, developing comprehensive datasets to enhance system adaptability, and refining classification models to address complex scenarios. The adoption of IoT, 5G, and cloud technologies holds promise for expanding system accessibility and applications in healthcare, education, and elderly care. By addressing these limitations, intelligent sitting posture monitoring systems can play a pivotal role in mitigating health risks associated with prolonged sitting and poor posture. This survey aims to contribute to researchers and engineers in ergonomics, healthcare, and IoT while inspiring continued innovation and practical advancements in posture monitoring technology.

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