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Systematic Review

A Systematic Review on Smart Insole Prototypes: Development and Optimization Pathways

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Abstract

This review synthesizes research on smart insole prototypes and their designs, focusing on those incorporating artificial intelligence (AI) and a wireless communication/transmission system. The main objective of this work is to summarize existing studies, identify key trends, evaluate the performance of these innovative biomechanical tools, and recognize the factors that could lead to optimization. This comprehensive analysis includes studies from PubMed, Scopus, and Web of Science databases and other investigations on the critical themes to consider. It follows strict inclusion and exclusion criteria, ensuring the quality and accuracy of the overview. The findings emphasize significant progress in smart insoles, particularly in AI-enhanced prototypes, while addressing existing challenges and problems. This review helps guide potential future research and define practical application directions. The growing importance of biomechanics, especially on smart insoles, underscores the considerable potential of these innovations to monitor and improve human movement in both clinical and non-clinical settings, promising a future of more effective and personalized health and performance interventions. This protocol was registered with the International Platform of Registered Systematic Review and Meta-Analysis Protocols (INPLASY) on 6 February 2025 and was last updated on 6 February 2025.

Keywords: smart insole; biomechanics; artificial intelligence; machine learning; design; prototype

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1. Introduction

Wearable sensors and smart devices have become a reality and a helpful tool that can provide essential information across various fields of study [1]. Smart insoles fall within this category of equipment, not only representing a cutting-edge development in wearable technology but also being specifically designed to monitor activity and enhance the performance of several motor functions through real-time data collection and analysis. This product is gaining popularity and becoming a preferable wearable device for everyday use. Furthermore, smart insoles can serve as an alternative to traditional technological gadgets such as the global positioning system (GPS) or smartphones when these are

unavailable or inaccessible [2]. Additionally, they offer significant advantages in terms of low cost and reliability [3].

The increasing popularity of smart insoles was driven by several factors, including advancements in technology, user-friendly signal processing algorithms, and machine learning (ML) techniques, alongside advances in new sensor technologies [2]. By collecting valuable data regarding motion, muscle activity, nerve responses, and pressure, these devices can analyze patterns and actions, enabling practical interventions, ergonomic improvements, and even more efficient prediction of disease development [4]. With the integration of AI, these devices have the potential to revolutionize patient care and athletic performance in a non-intrusive way and with daily confidence [3]. The junction of these technologies can even help in the disease rehabilitation process and provide rehabilitation in the comfort of patients' homes [4]. However, despite these advantages, gaps and opportunities for improvement persist across all applications of this technology. For example, nowadays, the known technology of wearable sensors for sports performance purposes has a few obstacles to overcome, such as the high cost, the high energy consumption, and the fitting [1].

This systematic review aims to provide a comprehensive overview of the methodologies employed in smart insole prototypes, focusing on AI's potential to enhance functionality and accuracy. We examine the objectives, processes, and outcomes of existing studies, identify critical gaps in the current literature and propose directions for future research.

2. Materials and Methods

In this review, a strategic approach was taken to select three databases for the search: PubMed, Scopus, and Web of Science. The chosen keywords, "smart insole", "artificial intelligence" or "machine learning", and "prototype" or "design", led to a certain number of hits, as shown in Table 1. The table provides the parameters and the essential information of the keywords and combinations used for the searches in the selected databases.

Table 1. Keyword combinations used for searches in the selected databases.

Database Name	Platform	Date Coverage	Date of Search	Search Within	Source Title	Command	# (No.) of Results
Scopus	Elsevier	–2024	17 September 2024	Article title, Abstract, Keywords	All	"smart insole" AND "artificial intelligence" OR "machine learning" AND "prototype" OR "design"	12
Web of Science	Clarivate	–2024	17 September 2024	All Fields	All	"smart insole" AND "artificial intelligence" OR "machine learning" AND "prototype" OR "design"	6
PubMed	NLB/NIH	–2024	17 September 2024	All Fields	All	"smart insole" AND "artificial intelligence" OR "machine learning" AND "prototype" OR "design"	1

This study followed the PRISMA [5] guidelines for systematic reviews and the protocol for this systematic review was registered on INPLASY (NO. 202520031). Thirty-nine works were included in the review; nineteen were retrieved from the three databases, and thirty were added manually. These last works resulted from the suggestions of the respective websites used for the research, and the suggestions were probably created by the algorithms due to each library's search history. Including these studies increases the review work and gives a better perception, justification, and knowledge of the referred authors' practical investigations and theoretical works. In this search strategy, it was agreed that restrictive

conditions should not be applied. Hence, it was decided to include articles, review articles, systematic review articles, conference papers, proceeding papers, and book chapters only written in English.

On the other hand, short communications were not included since, from a group perspective, they do not offer benefits and value to the study. Next, there were no restrictions or imposed conditions regarding the publication year. Studies were selected based on the predefined inclusion and exclusion criteria mentioned above, focusing on those that detailed AI-enhanced smart insoles' methodologies, manufacture, design and performance metrics. Figure 1 presents the PRISMA flow diagram, illustrating the screening procedure followed. The choice of the selected databases ensured that low-quality and low-impact articles were not considered.

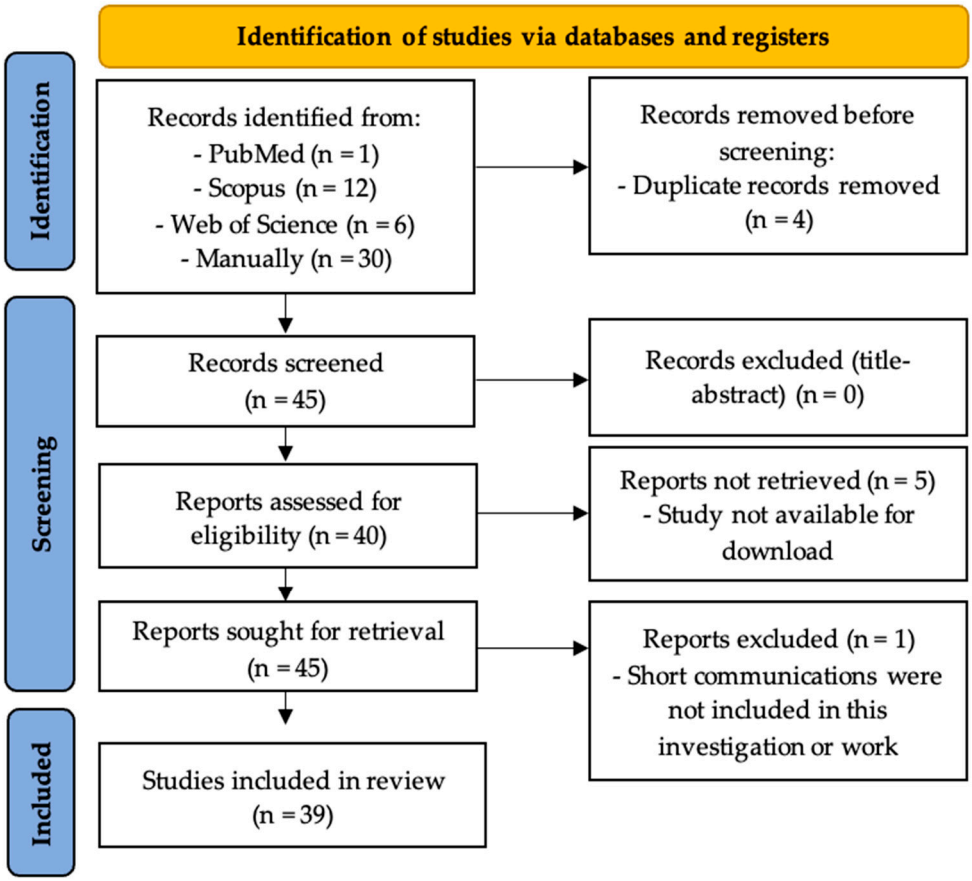

Figure 1. PRISMA flow diagram.

Four duplicate records were excluded from the total number of works searched, five reports were unavailable for download and consultation, and finally, one short communication was excluded in this review.

Figure 2 provides a detailed analysis of the type of documents used in this investigation. As stated previously, the specificity of the subject and the decision not to apply many conditions resulted in gathering various documents.

As explained previously, the specificity of the research and the decision not to apply many restrictions resulted in gathering several documents. The number of articles included in this work was twenty-four, followed by seven reviews, five conference papers, and three systematic reviews. Incorporating a more comprehensive range of source types is essential to encompass a more extensive array of academic views and perspectives, thus enhancing the strength and thoroughness of the study's conclusions. In the next figure it is possible to observe the year of publication of the works selected for this study.

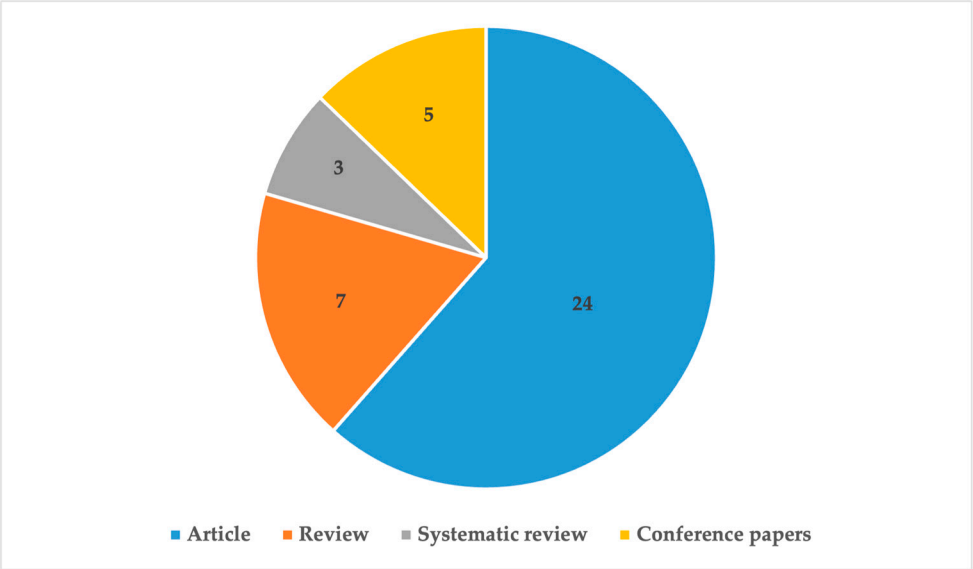

Figure 2. Information of the document types included in this systematic review.

The data shown in Figure 3 make it easy to conclude that interest in this subject increased exponentially in 2017 compared to 2012 and from 2022 to the present. Another fact is that the sum of the records in 2022, 2023, and 2024 represents about 67% of the total number of works. This last knowledge demonstrates that this study is in line with the research's interests.

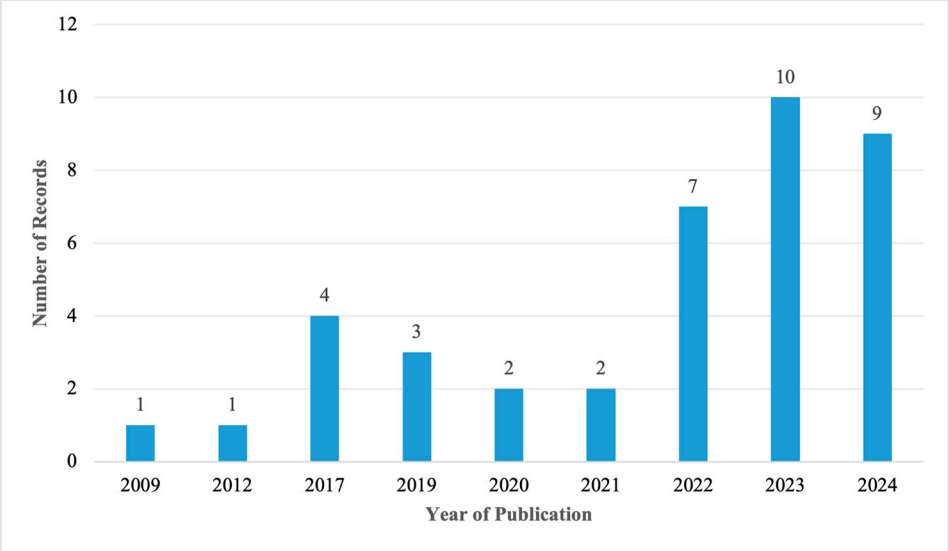

Figure 3. Information related to the publication year of the documents included in this systematic review.

In the first map generated with the VOSviewer software (Version 1.6.20 (0)), which is presented in Figure 4, the keywords included in the thirty-nine works included in the research are observed. The appearance of keywords like "wearable sensor", "plantar pressure", "ground reaction force", "model", "center of pressure (CoP)", "gait", "algorithm", "real time" and/or "development" serves as a strong validation of the chosen methodology of database search. However, it is important to note that other terms that appear with highlights, like "diabetic foot insole" and "research," could be present because most of the studies and prototypes have applications in the healthcare field. All the clusters presented have a specific color. It is evident that the red cluster focuses on technological development with applications in the healthcare field, including keywords such as "development",

"wearable sensor", "algorithm", and "diabetic foot insole". The purple cluster features terms such as "plantar pressure", "shoe", "importance", and "real time", emphasizing the importance of real-time plantar pressure measurement. Keywords such as "part", "speed", "detail", and "PETG" belong to the yellow cluster and are related to the 3D printing and material properties. The green cluster includes "ground reaction force", "model", "research", and "sensorized insole", and the following keywords are linked to biomechanical analysis and modeling. Finally, the blue cluster links terms associated with gait analysis, such as "gait", "center", "CoP", "layout", and "flex sensor".

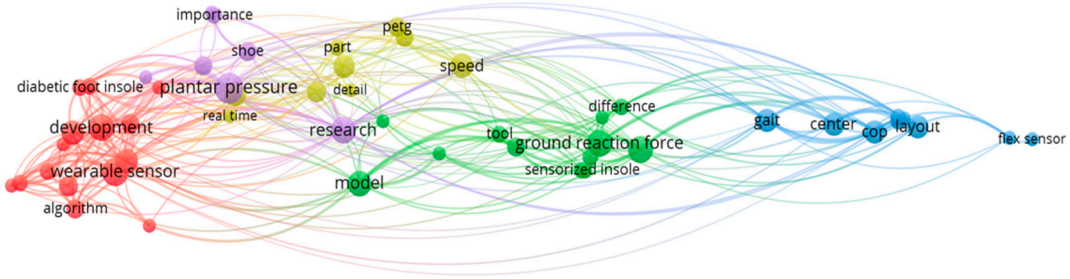

Figure 4. Complete counting keywords network visualization.

This graphic representation was achieved by creating a network visualization with three minimum occurrences, which provided a map with five clusters and a total of fifty-two terms. However, other words are inherent to the keyword search, and their presence confirms the depth of the subjects and the value of the gathered studies. The purpose of this study is related to sensor technology, applications, materials and designs, machine learning, and other types of artificial intelligence and prototypes. It is safe to conclude that most of the keywords presented in this map are incorporated in one form or another in the subjects previously referred to.

Figure 5 presents a keyword density visualization. This type of representation allows one to make quick observations and comparisons regarding the number of times (quantity) that a certain keyword appears in the selected works. So, to analyze correctly, it is important to be aware of the intensity and brightness of the color, the area length and the font size. In conclusion, it is safe to say that "ground reaction force", "plantar pressure", "development" and "wearable sensor" have a higher number of occurrences compared to the others. However, it is also visible through this type of image or representation that the keyword "algorithm" does not have many occurrences; on the other hand, it is possible to verify that the keyword "model" appears to have a higher frequency of appearance, and it can be considered that there is a direct link and connection between the two terms.

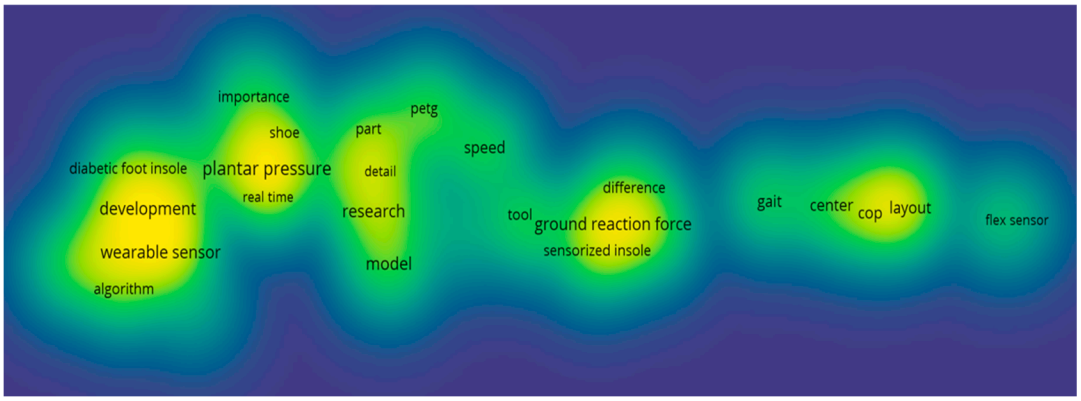

Figure 5. Complete counting keywords density visualization.

In Figure 6, the keyword network visualization images show remarkable similarities, underscoring the value of this data representation. The primary purpose of this visualization is to reveal the connections between keywords and the year of publication. A closer examination shows that the brightness of the color indicates the recency of the keyword's occurrence. For example, keywords like "diabetic foot insole" and "importance" are prominent in more recent works, while others like "algorithm", "model" and "real time" have been consistently present since 2022, providing a valuable historical context. This can occur for the same reasons stated in the Figure 4 analysis. However, it is noticeable that these terms are current and appear more frequently due to the diabetes pandemic and thus the number of patients suffering from such conditions.

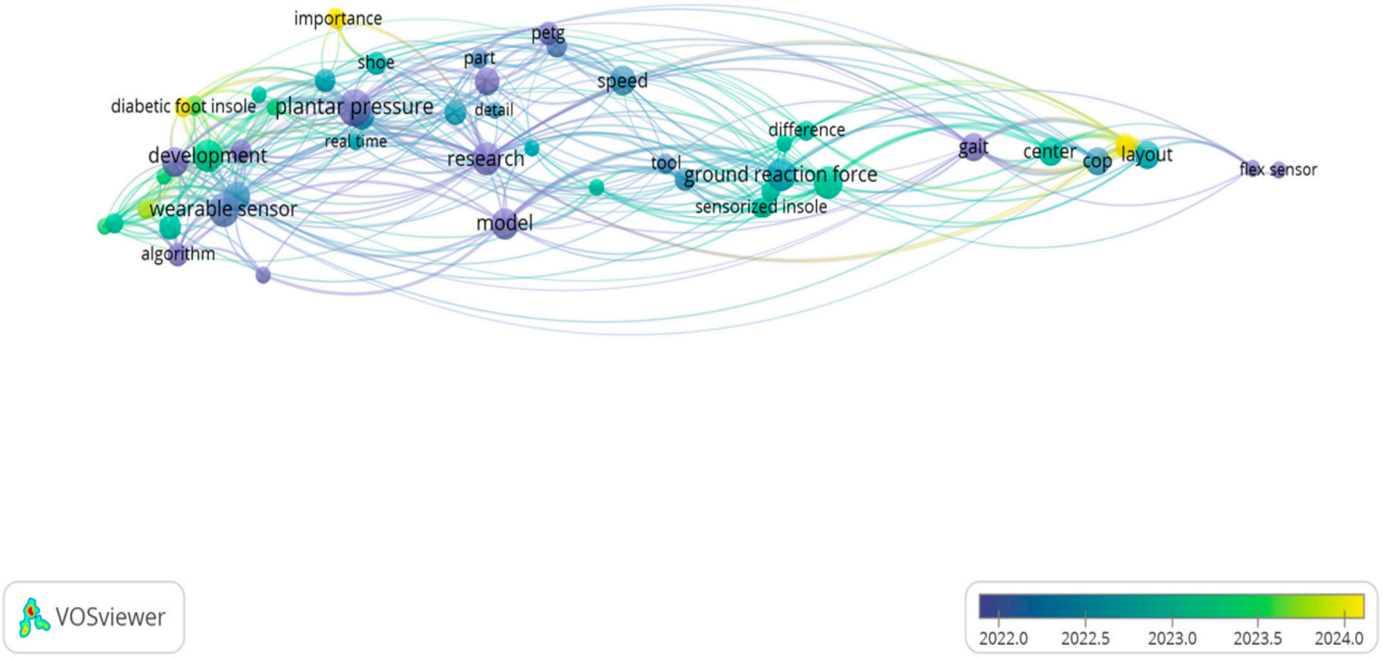

Figure 6. Complete counting overlay visualization.

3. Results

In all the investigations presented above in Table 2, some information is visible about the insole manufacturing materials, types and numbers of sensors, and hardware and software used, and if they integrated a wireless system or any type of AI. Five worked on devices already available in the market of the twenty-six studies, and the rest labored on their prototypes. Between all of them, ten integrated a wireless system, two implemented AI in the equipment and eight presented a smart insole system with wireless and AI.

According to the information provided in all investigations, studies and works, regarding the smart insole prototypes with wireless connection, the 3D-printed capacitive insole [6] and the PDMS-based capacitive sensor insole [7] demonstrated superior performance, making them the most effective for high-precision plantar pressure and gait monitoring applications. The 3D-printed capacitive insole demonstrated sensitivity of 1.19 MPa^{-1}, an operating pressure range of 41.5–872.4 kPa, excellent linearity (R^2 = 0.993), fast response and recovery times (142–160 ms), durability over 2280 cycles, and low hysteresis (<10%). It also offers practical solutions for stable operation across gait speeds of 30–70 steps/min. Complementarily, the PDMS-based capacitive insole showed high resolution, linear pressure response, and superior mechanical stability under both controlled loading and gait conditions, with a reported sensitivity of 0.020 pF/kPa for 3 mm thick sensors.

Table 2. Prototype specifications developed in retrieved studies.

Authors	Insole Manufacturing Materials	Types of Sensors	Number of Sensors	Microcontrollers (Hardware)	Power Supply (Hardware)	Communication/ Transmission (Hardware)	Software Programs	Wireless (Yes (Y)/No (N))	AI/ML Techniques (Yes (Y)/No (N))
Sorrentino et al. (2020) [8]	Flexible printed circuit boards/dielectric layer, 3D-printed support made of plastic with gaps and conductive Lycra	Capacitive (pressure and temperature)	336 (280 + 56) each insole	Microcontroller tactile board (MTB)	Connection to a host computer through a controller area network (CAN) bus interface	MTBs—host computer—CAN	MATLAB (process and visualize data) (The Mathworks Inc., Natick, MA, USA), YARP protocol (stream data), qpOASES (C++ software package)	N	N
Ho et al. (2022) [9]	Textile pressure sensor (W-290-PCN)	Capacitive	10 per insole	Capacitance to Digital Converter (CDC)	ND *	ND *	MATLAB R2021a (The Mathworks Inc., Natick, MA, USA)	Y	N
Eguchi, R. and Takahashi, M. (2023) [10]	FlexiForce A301 (Tekscan, South Boston, MA, USA), insole-shaped polyethylene terephthalate sheet using polytetrafluo-roethylene tape	Force-sensing resistors	15 each	mbed NXP (LPC1768, Arm, Cambridge, UK)	ND *	Radio module (XBee, Digi International, Hopkins, MN, USA), op-amps (LMC6484AIM, Texas Instruments, Dallas, TX, USA), 12-bit analog-to-digital (A/D) converters (MCP3204T-BI/SL, Microchip Technology, Chandler, AZ, USA), a microSD card (Transcend, Taipei, Taiwan)	MATLAB (The Mathworks Inc., Natick, MA, USA)	N	Y

Table 2. *Cont.*

Authors	Insole Manufacturing Materials	Types of Sensors	Number of Sensors	Microcontrollers (Hardware)	Power Supply (Hardware)	Communication/ Transmission (Hardware)	Software Programs	Wireless (Yes (Y)/No (N))	AI/ML Techniques (Yes (Y)/No (N))
Haron et al. (2024) [11]	Flexible silicone insole, phenolic sheet stiffener	Strain gauge rosettes, FlexiForce normal pressure sensors	6 (3 + 3) each	Teensy 4.1 32-bit microcontroller (PJRC Electronic Projects, ARM Cortex-M7 processor, Portland, OR, USA)	3.7 V 3500 mAh Lithium Polymer battery (LP104567, EEMB, Moscow, Russian Federation), linear regulator (LDO, B08HQQ32M2, DollaTek, Hong Kong, China)	Analog-to-digital amplifier (HX711 ADC, HALJIA, Zhongai, China), ESP8266 UART WiFi adapter (Espressif Systems, Shanghai, China)	MATLAB (The Mathworks Inc., Natick, MA, USA)	Y	N
Peyer et al. (2017) [12]	F-Scan VersaTek wireless insole system (Tekscan, Boston, MA, USA)	Pressure sensors	960 each	mbed NXP LPC1768	ND *	F-Scan VersaTek wireless insole system, Motive's sync output	MATLAB R2014a (The Mathworks Inc., Natick, MA, USA)	Y	N
Lakho et al. (2022) [13]	Insole with 3 layers: A commercial shoe insole (not specified), a Polyvinyl Chloride (PVC) insole with the sensors and a fabric layer	Flexi force sensor and resistive flex sensor	5 (4 + 1) each	ND *	ND *	Bluetooth module and USB connection panel (not specified)	ND *	Y	N
Luna-Perejón et al. (2023) [7]	Insole with 3 layers: Ground layer (not specified), a flexible Polydimethylsiloxane (PDMS)-based dielectric layer, and last layer with the measurement electrodes	Capacitive sensors were made using PDMS as the dielectric material	12 each	STM32L432KC microcontroller with an Arm Cortex-M4 MCU	two 7.4 V LiPo batteries	Bluetooth module (HC-06), AD7147-1 capacitance-to-digital converter (CDC)	ND *	Y	N
Ciniglio et al. (2021) [14]	Pedar-X®, Novel, 100 Hz	Capacitive pressure sensors	99 each	ND *	ND *	ND *	Novel EmedLink, MATLAB 2018b (The Mathworks Inc., Natick, MA, USA)	ND *	N

Table 2. *Cont.*

Authors	Insole Manufacturing Materials	Types of Sensors	Number of Sensors	Microcontrollers (Hardware)	Power Supply (Hardware)	Communication/ Transmission (Hardware)	Software Programs	Wireless (Yes (Y)/No (N))	AI/ML Techniques (Yes (Y)/No (N))
Khandakar et al. (2022) [15]	(not specified)	Force-sensitive resistor (FSR) sensors and thermistor-based temperature sensors	24 (16 + 8) each	ESP32 TinyPico	Lithium Polymer (Li-Po) batteries	Bluetooth Low Energy (BLE)	Arduino software and a Python-based Real-Time Data Logger	Y	N
Lin et al. (2017) [16]	Advanced conductive eTextile fabric coated with a piezoelectric polymer. The insole also contained a flexible Printed Circuit Board (PCB) that housed the microcontroller	Pressure sensors and Inertial Measurement Unit (IMU)	48 + 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer	CC2541 microcontroller (Texas Instruments)	Rechargeable battery (not specified)	BLE module	ND *	Y	Y | Action Manifold Learning (AML) framework
Matthies et al. (2017) [17]	Electrodes attached to a laser-cut polyacrylate sheet, a compressible foam plastic layer that acts as dielectric, a flexible plastic sheath as a protector of the electrodes and a silicone insole	Capacitive pressure sensors	6 each	Arduino Nano microcontroller	Lithium Polymer (Li-Po) battery	BLE module	Arduino IDE, CapSense library, Weka tools	Y	Y | ML techniques (classifiers such as, Random Forest (RF), Bayes Net (BN), Naive Bayes (NB), Instance Based Learner (IBK), and Sequential Minimal Optimization (SMO)
Ishtiaque et al. (2022) [18]	Plastic housing for the electronics	Pressure sensors	ND *	ND *	ND *	Narrowband Internet of Things (NB-IoT)	Custom mobile application	Y	Y | ML (Neural Networks (NNs))
Yang et al. (2017) [19]	Sennotech Insole X, Sennotech Inc.	Pressure sensors and IMU	16 + 3-axis accelerometer, 3-axis gyroscope, 3-axis magnetometer	Microcontroller Unit (MCU) (model not specified) and integrated with a 16 to 1 channel multiplexer (MUX)	Battery module (model not specified) rechargeable via USB	BLE module	Smartphone application with graphical user interface and cloud server hosts a TUG data analysis module	Y	Y | ML techniques (not specified)

Table 2. *Cont.*

Authors	Insole Manufacturing Materials	Types of Sensors	Number of Sensors	Microcontrollers (Hardware)	Power Supply (Hardware)	Communication/ Transmission (Hardware)	Software Programs	Wireless (Yes (Y)/No (N))	AI/ML Techniques (Yes (Y)/No (N))
Eldrige et al. (2019) [20]	NA	Pressure sensors	4 each	ND *	ND *	ND *	Smartphone application, ML-based analysis module, Edge computing software, Microsoft Kinect and OpenPose	Y	Y | ML techniques (RF, Decision Tree (DT), Support Vector Machine (SVM), k-Nearest Neighbors (k-NN), Gradient Boosting (GB))
Ivanov et al. (2019) [21]	Sensors were affixed on a flexible printed circuit board inserted between two flexible polyvinyl chloride sheets	Force sensors (FlexiForce A301) and inertial sensor (BMI160)	9 + 1 each	nRF52832 (by Nordic Semiconductor)	Rechargeable battery (2.5 V)	BLE, 12-bit ADC (ADS7042)	GaitPy	Y	Y | ML technique (RF classifier)
He et al. (2021) [22]	piezoresistive carbon nanotube conductive films, silver-plated conductive yarn (by Jinan Yumo Technology and Trade Co., Ltd. (Shandong, China)), Ethylene-vinyl acetate copolymer (PEVA) foam insoles (by Jinjiang Jinyi Shoe Material Co., Ltd. (Fujian, China)), Fusible interlining (by Dongguan Yufang Interlining Co., Ltd. (Guangdong, China))	Wearable textile-film sensors	5 each	ND *	ND *	ND *	LabView	N	N

Table 2. *Cont.*

Authors	Insole Manufacturing Materials	Types of Sensors	Number of Sensors	Microcontrollers (Hardware)	Power Supply (Hardware)	Communication/ Transmission (Hardware)	Software Programs	Wireless (Yes (Y)/No (N))	AI/ML Techniques (Yes (Y)/No (N))
Burch et al. (2023) [23]	Carbon nanotube (CNT)-based pressure sensors, textile substrate, conductive threads	Textile-based pressure sensors (piezoresistive sensors)	8 each	Arduino Uno Rev3, microSD card and adapter	ND *	ND *	Arduino IDE, MATLAB (The Mathworks Inc., Natick, MA, USA)	N	N
Jiang et al. (2024) [24]	NA	Pressure sensors, IMU, MoCap	230 + 2 + 2 each	ND *	ND *	BLE	ND *	Y	Y | ML technique (NN, Linear Discriminant Analysis (LDA))
Lueken et al. (2020) [25]	NA	Force-sensing resistors (FSRs)	4 FSR402 sensors each	CC1310 wireless microcontroller (by Texas Instruments)	230 mAh lithium-ion battery	868 MHz radio communication interface, 12-bit ADC MCP3204 (Microchip Technology Inc., Chandler, AZ, USA)	ND *	Y	N
Samarentsis et al. (2020) [6]	3-layer sensors: Protopasta CDP11705 composite conductive PLA (top and bottom), Filaflex 70A TPU; 2-layer insoles: Filaflex 82A (upper and lower layer)	3D-printed capacitive pressure sensors	16 each	2x Arduino Nano system boards (Arduino LLC, Boston, MA, USA)	ND *	Stepper motor (Nema 23 57BYGH115 from Wantai motors), motor driver (TB6600), microdisplay (1300 OLED Display Module from Waveshare)	Fusion 360 CAD (Autodesk, San Rafael, CA, USA), Ultimaker Cura 4.6.2 (Ultimaker B.V., Utrecht, The Netherlands), Graphical User Interface (GUI), Arduino IDE	Y	N
Zheng et al. (2023) [26]	3-layer insole-shaped sensing unit: The upper triboelectric layer is made of poly-dimethylsiloxane (PDMS) and has 44 hollow grooves. The middle layer consists of Cu electrodes and the bottom has polyimide layer	Triboelectric nanogenerators (TENG)	44-pixel TENG-based sensor array each	2x STM32F427	Self-powered using TENG	ADC, multichannel data acquisition (DAQ) board, SD card	ND *	N	N

Table 2. *Cont.*

Authors	Insole Manufacturing Materials	Types of Sensors	Number of Sensors	Microcontrollers (Hardware)	Power Supply (Hardware)	Communication/ Transmission (Hardware)	Software Programs	Wireless (Yes (Y)/No (N))	AI/ML Techniques (Yes (Y)/No (N))
Crossland et al. (2023) [27]	Strain Analysis and Mapping of the Plantar Surface (STAMPS). 3 layers: a 5 mm thickness plasticine slab, a cross-patterned Nylon mesh, and an optimized computer-generated stochastic speckle (Correlated Solutions Speckle Generator, v1.0.5)	-	-	ND *	ND *	ND *	Digital Image Correlation (DIC), MATLAB (R2021b)	N	N
Gupta et al. (2023) [28]	3D-printed flexible insole (PLA), Velostat®, a polyethylene–carbon-black-infused composite material, Copper adhesive tape, Two layers of medium-density EVA (Ethylene–vinyl acetate), and high-quality leather	Piezoresistive pressure sensors made with Velostat®	5 each	ESP32	600 mAh lithium-ion battery	BLE	SolidWorks 2020, Mondopoint system, Arduino IDE, custom mobile app	Y	N
Fuchs et al. (2024) [29]	Pedar-X insole (Novel Electronics Inc., Saint Paul, MN, USA)	Capacitive sensors	99 each	ND *	ND *	ND *	Vicon Nexus 2.10.1 software, PASW Statistics 18.0 (SPSS Inc, Chicago, IL, USA) and Excel 365 (Microsoft Corporation, Redmond, WA, USA)	Y	N

Table 2. *Cont.*

Authors	Insole Manufacturing Materials	Types of Sensors	Number of Sensors	Microcontrollers (Hardware)	Power Supply (Hardware)	Communication/ Transmission (Hardware)	Software Programs	Wireless (Yes (Y)/No (N))	AI/ML Techniques (Yes (Y)/No (N))
Choi et al. (2024) [30]	F-Scan system and low-cost insole sensors	FSR sensors	6 each	ND *	ND *	ND *	ML models	Y	Y | Recurrent Neural Networks (RNNs), Long Short-Term Memory (LSTM)
Willemstein et al. (2023) [31]	3D-printed sensors: soft foam layer with the sensor, two insulating (top and bottom) layers, and a layer with grounding electrodes	Piezoresistive porous (foam-like) sensors	4 each	Arduino Uno (Arduino AG, Italy)	ND *	16-bit analog-to-digital converter ADS1115 (Texas Instruments, Dallas, TX, USA), breakout board (Adafruit, NY, USA) laptop	MATLAB (The MathWorks, Natick, MA USA) System Identification Toolbox	N	Y | Hammerstein-Wiener (HW) model

ND * = No data.

Some studies like the ones that are mentioned next do not provide much information about the materials used and procedures adopted. Crossland et al. [27] innovated a speckle-patterned system for strain analysis, utilizing digital image correlation; He et al. [22] created piezoresistive sensors using carbon nanotube conductive films and ethylene vinyl acetate (EVA) foam insoles; and Ciniglio et al. [14] and Fuchs et al. [29] employed commercial systems like Pedar-X and F-Scan for advanced analysis.

Regarding the smart insole prototypes with wireless connection, the 3D-printed capacitive insole [6] and the PDMS-based capacitive sensor insole [7] demonstrated superior performance, making them the most effective for high-precision plantar pressure and gait monitoring applications. The 3D-printed capacitive insole accomplished high scores in sensitivity, stability, and linearity, accurately distinguishing gait phases in real time. This device also offered strong reliability with low hysteresis and rapid response, making it well-suited for dynamic gait analysis. The PDMS-based capacitive sensor insole prototype presented a smooth composite material, a linear response, and precise and consistent pressure readings across different foot regions. Together, these two prototypes provide robust solutions for accurate real-time plantar pressure monitoring.

In recent investigations of prototypes with AI but no wireless capability, the focus was on studying ground reaction forces (GRF). Eguchi et al. [10] implemented the ML technique Gaussian Process Regression in an insole with pressure sensors. The results were accurate and appropriate for clinical trials and daily life. Willemstein et al. [31] presented a prototype with 3D-printed porous piezoresistive sensors in a commercial insole and with the employment of Hammerstein–Wiener models. According to the study, this device was a viable alternative compared to other commercial options due to its scores and cost.

The various studies incorporating wireless transmission and AI technology revealed significant improvements to diverse fields of knowledge and applications. For instance, the study on low-cost smart insoles employing recurrent neural networks enhanced GRF and CoP predictions by over 30% compared to traditional methods, showing promise for cost-effective gait analysis in clinical and day-to-day life [30]. The CapSoles system reached 95% accuracy in user identification and 82% in distinguishing floor types using capacitive sensing [17]. Another study involving a sensor insole designed for gait analysis achieved a remarkable 98.75% user recognition accuracy, underscoring its potential for sports and healthcare, where precision is critical [21].

An AI-powered smart insole developed for the construction industry [17] also demonstrated practical utility in reducing back pain risk among older workers by providing real-time feedback on lifting techniques. However, improvements in robustness are still needed for commercial purposes [18]. The smart insole timed up and go (SITUG) system, tailored explicitly for elderly users, refined the timed up and go test to operate in complex environments with a mean accuracy of 94.1% for gait feature extraction, making it a powerful tool for fall-risk assessment [19]. Meanwhile, the MovePort dataset introduced an extensive multimodal dataset that includes electromyography (EMG), IMU, and insole pressure sensors, enabling advanced analysis of abnormal movements in rehabilitation and setting a foundation for clinical research [24]. In the healthcare domain, a study leveraging pressure-map manifold learning achieved 86.6% accuracy in patient handling activity recognition, addressing injury risks for caregivers through robust task monitoring [16]. Lastly, a novel approach combined smart insoles with red–green–blue (RGB) cameras for identifying stationary individuals based on posture, presenting a feasible solution for IoT environments with controlled user monitoring [20]. Among these, the insole designed for gait analysis and the SITUG system obtained the best scores, presenting high accuracy and offering impactful resolutions in overcoming critical problems in healthcare and sports.

The studies presented demonstrate significant strides in integrating innovative materials, sensor designs, wireless technologies, and AI-driven frameworks. These advancements underscore the potential for developing advanced wearable technologies, which could enable real-time data collection and enhanced functionality across various applications.

4. Discussion

As expected, with the evolution of technology and the progress made in the smart insole field, it is essential to segment the final product to understand the components better while always understanding its purpose and future application. It is necessary to study the several manufacturing materials methodologies, the sorts of hardware, the database size, the numbers and types of sensors, and, ultimately, the integration of different ML techniques.

It is also known that smart insole devices evolve toward simplified designs, and the device's power consumption will be lower. Applications for daily use mainly focus on monitoring, detection, and interactions. It is desirable to have a streamlined design with the minimum number of sensors integrated, as the cost, power consumption, and robustness are the top considerations [2].

4.1. Insole Manufacturing Materials

Three very important features in this subchapter need to be addressed to better understand the procedures that come with it. First, different kinds of materials are already used in the production of insoles. For the manufacture of orthotics, various materials can be used, such as plastics (e.g., polypropylene), foams (e.g., polyurethanes and EVA), and carbon-based composite materials (e.g., carbon-fiber-reinforced plastics). It is crucial to carefully select the appropriate materials, considering that an excessively stiff insole will not provide adequate impact absorption, while an overly soft insole will lack sufficient support [32]. Among the materials mentioned, Valvez et al. [33] demonstrated that the mechanical properties of Poly(ethylene terephthalate)-glycol (PETG) can be significantly improved by optimizing printing parameters such as nozzle temperature, layer height, and infill density. Their findings reinforce the importance of process parameter tuning in additive manufacturing to ensure structural integrity and enhance mechanical performance [34]. In fact, in sensor applications, the structural integrity of the printed substrate is often a prerequisite for consistent and reliable signal response. Parameters such as layer thickness and infill density not only influence mechanical strength but also affect deformation behavior, dimensional stability, and interlayer bonding—all of which can impact the performance and durability of embedded or printed sensing elements [35]. Therefore, even when the final application is functional, structural optimization remains a critical foundation. Insoles with one single layer focus essentially on comfort, whereas insoles with two layers usually combine both soft and stiff materials to provide comfort and support to the user. Multi-layered insoles go one step further, incorporating various materials to balance support, control, and comfort. Thus, each structure and material choice affects the manufacturing process and therefore the insole performance in unique ways [36].

Second, it is also possible to choose a variety of manufacturing processes to fabricate a desired insole. There are various AM technologies such as selective laser sintering (SLS), selective laser melting (SLM), stereolithography (SLA) and fused filament fabrication (FFF) [36].

Finally, it is important to know the application or purpose of the equipment. As stated in Crabtree et al.'s [32] study, which focused on methodology of design and manufacture of sports insoles and referred to this niche as the symptom-specific sports (3S) insole, these processes must include the application or the specification of the sport to the equation. In

that order, is important to prescribe the insole according to the geometry and biomechanical requirements, and to consider the specific sport (as well health problems, disabilities and disorders). This final point is important because the plantar pressures might differ and so the inherent sports movements can be characterized considering the loading patterns. Therefore, customizing insole design to match individual foot characteristics is essential to reduce the risk of pain and injury [36]. One task that can be implemented and could influence the outcome of the final product is the usage of three-dimensional foot-scanning equipment to reach a proper and accurate prescription of the foot insole [32]. In Figure 7, we show the synthetized information and the possible steps to obtain an adequate 3S insole.

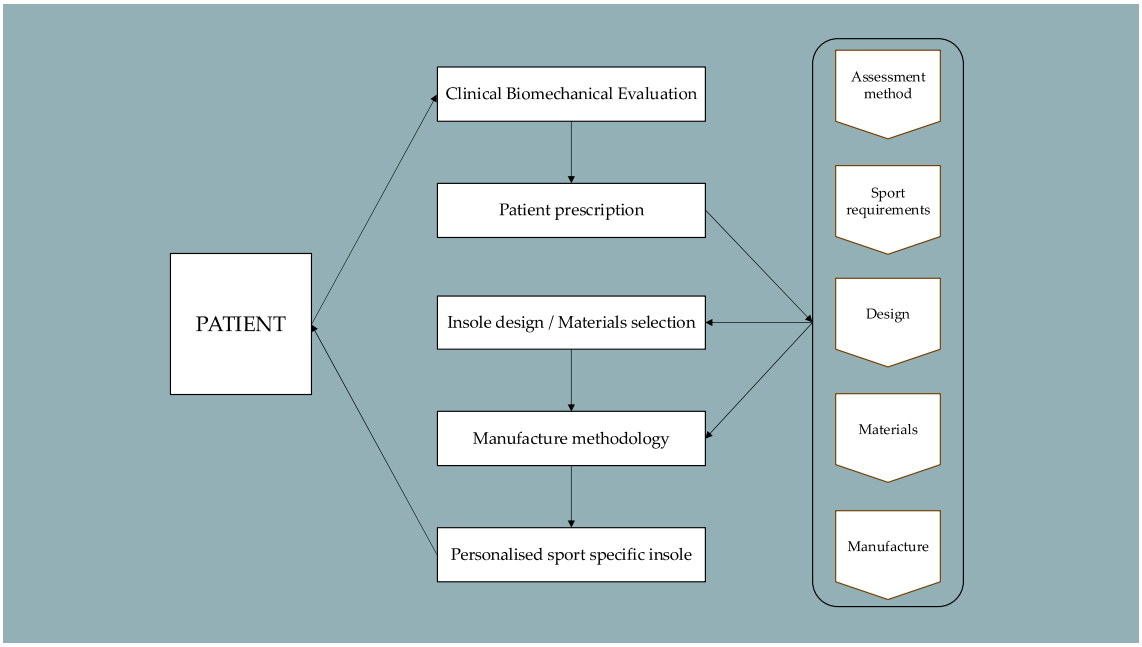

Figure 7. Adaptation of an image in Crabtree et al. [32] about a prescription methodology for a 3S insole.

4.2. Significance of Hardware

Choosing and integrating hardware components such as sensors, microcontrollers, batteries, and communication modules are crucial in the process of smart insole development. As is known, because of the inconvenience and impracticality of using force platforms as the main and preferable tool to measure GRF outside of laboratory settings, most studies have been constrained to indoor environments [3].

To overcome some obstacles, the precision and durability of the smart insole's elements determine the accuracy of data collection, which is essential in several applications. For example, high-quality sensors that can gather pressure points and force distribution allow users or healthcare providers to analyze gait patterns or detect early signs of foot-related health issues. Meanwhile, a compact but minimal, energy-efficient microcontroller is essential for processing data, ensuring the user's comfort.

Battery capacity, durability, and wireless communication capabilities are equally important; these specifications affect the range of the insole that can operate and how effectively it can transmit data to other devices, such as smartphones or computers. To transmit data to a computing platform in proximity, different technologies can be chosen and used, such as near-field communication (NFC), Bluetooth, Adaptive Network Topology (ANT) protocol, BLE, and ZigBee. Wireless communications, such as high-speed packet access (HSPA) or long-term evolution (LTE) services, can also be chosen [2].

4.3. Size and Type of Data

Full-body activities can be accurately recognized by smart insoles when compared to smartwatches and smartphones. Postures and movements like laying down, sitting, standing, walking, climbing staircases, running, cycling, and driving are possible to detect when using this type of technology. The non-obtrusive specification of the smart insole (if considered) permits the collection of different types of data, like the measurements of ground reaction force distribution, which can be valuable to disease detection and diagnosis [2]. Moreover, the integration of cycle time and activity repetition data could be instrumental in fatigue prevention initiatives [3].

Variables like the duration and the length of strides, steps, stances, swings, double supports, speeds, and cadences are also used to identify gait cycles. Gait spatiotemporal parameters represent the basics of gait analysis and are essential for balance, postural stability, and athletic performance evaluation. In conclusion, gait accuracy directly depends on spatiotemporal parameters and contributes to the overall gait detection accuracy [2].

One of the problems identified by most of the authors who were cited in this investigation is the lack of data diversity. For instance, some researchers have conducted pressure tests on diabetic foot insoles using the Pedar system [36] and others have recruited only college students [2]. Therefore, conducting a study with a diverse sample can be an asset, as it can help yield different conclusions and provide insight into the actual value of this technology. However, this can be an obstacle; there is evidence that models trained on small datasets, particularly in cases involving nonparametric regression, often perform best [37]. It is crucial to acknowledge that overtraining the data sample can contribute to this problem.

4.4. Types and Numbers of Sensors

It is known that among available sensors, each one has its own specifications, and considering the application and need, it is possible to choose the more appropriate one.

According to Razak et al. [38], to gather precise and accurate biomechanical data, it is first necessary to optimize the technology to the purpose, nature and application. Foot plantar sensors also need to fulfill some requirements such as mobility; limited wiring or wireless function; 15 sensors to cover most of the body weight changes; low cost; and low power consumption. To achieve good performance it is important to follow some key specifications, like hysteresis (the response when the sensor is loaded and unloaded), linearity (the response of the sensor to the applied pressure), sensing size, pressure range, temperature sensitivity, operation frequency/sampling and creep and repeatability (deformation of the material under high temperature and static stress and the ability to produce reliable results after a long period of time, respectively).

Recent studies concluded that IMU and pressure sensors are the most used in insoles for sports performance and rehabilitation [4,39]. In addition, there has been an increase in the integration of sensors into medical devices. With that said, it is also crucial to determine the adequate position and be precise in the sensor placement. Further calibrating it/them properly and proceeding to validation is essential [40].

Among the different types of sensors, triboelectrics can benefit from being self-powered, and according to a study by Fazio et al. [1] this technology is often applied to detect pressures from different body parts. Subsequently, in 2022, Almuteb et al. [2] stated that real-time pressure distribution monitoring insoles with piezoelectric nanogenerators combined with a triboelectric–electromagnetic nanogenerator and triboelectric nanogenerator-powered smart insole have the advantage of being self-charging or battery-free for daily use and the ability to use the energy generators as pressure sensors.

However, it is important to consider that integrating multiple sensors to gain the most critical information often results in redundant data, bulky designs, and uncomfortable equipment [2]. As another solution, integrating regression techniques may provide a viable alternative by allowing the use of a reduced number of sensors for estimating biomechanical time series and measuring all required independent variables [35].

4.5. Integration of ML Techniques and Others

ML is one AI subset. To better understand this, this technique uses statistical models and algorithms to enable computers to execute specific tasks without explicit programming, focusing primarily on making predictions or decisions based on data. Inside the world of ML, there exist great tools like Supervised Learning and Unsupervised Learning. In the first tool, the model is trained on labeled data to predict outcomes for new and unseen data. The other is used mainly to discover patterns in input data that are not labeled and is often used for clustering or association tasks [41].

The commonly used ML algorithms for daily activity recognition are Support Vector Machine (SVM); Decision Tree; Naïve Bayes; Nearest Neighbor (NN); Random Forest; and Deep Learning, such as Convolutional Neural Networks [2,4].

Regarding the recent curiosity about ML, fewer investigations into integrating this technology exist, but it has been proven that it has advantages. Incorporating a non-fixed machine learning algorithm is better than other algorithms [4]. They can handle large and complex datasets, "learn" from data, constantly improve their performance, and identify patterns and relationships in data that may not be readily noticeable with traditional methods. To better understand the integration of ML algorithms in devices, the process includes several steps: (1) collection of raw data; (2) filtering the noise/cleaning the data; (3) applying extraction techniques; (4) training the dataset; and (5) applying the model. The training process involves adjusting the model's parameters to reach a prediction with a higher accuracy score when compared to the actual output. Once the model has been trained with attention, it can predict unknown data [41].

In Abdollahi et al.'s [3] study, the authors reached the conclusion that the NN and SVM models were the most used but also showed consistently high performance when applied to smart insole data. These two models are more effective and suitable for smart insole applications. Employing force and pressure sensors with associated signal processing algorithms in smart insole devices has been well explored. The change in foot pressure when standing, walking, and exercising has proven valuable in gait studies. Also, some studies demonstrated that the integration of ML to classify and recognize activities achieved high accuracies [2]. In Yamaguchi et al.'s [42] study, a regression model was applied in a shoe sole sensor system to predict GRF. The results were compared with the values obtained in a force plate and the authors observed a 15% lower root-mean-square error (RMSE).

4.6. Limitations

This review synthesizes information from 39 studies focused on smart insole prototypes, with some of them integrating AI and wireless technologies. The potential impact of these studies on healthcare and other fields is significant. However, several limitations must be acknowledged. The level of detail provided by the original studies varies significantly, particularly in terms of dataset size, subject diversity, sensor calibration methods, and real-time validation. As a result, it was not always possible to provide a structured comparative analysis of all key parameters such as model performance metrics, dataset characteristics, or overfitting risks. Additionally, many studies were conducted in controlled environments, which may limit generalizability to real-world conditions. Finally, various prototypes were

evaluated in research settings, and few have undergone clinical trials or large-scale user testing, which are critical steps toward commercialization and long-term adoption.

5. Future Directions

In a number of studies, significant issues have been identified, and connections have already been established. For instance, in 2012, Razak et al. [38] highlighted the necessity of a wireless system to deliver real-time and dependable foot plantar pressure data. The proposed solution to address the common issue was to minimize the hardware size and embed it within the shoe's insole along with the entire sensor. This detailed proposal called for a low-power, wearable wireless system, utilizing customized micro-electromechanical (MEMS) sensors and interfacing them with a data acquisition (DAQ) unit, to be integrated into the insole.

Another crucial specification in developing insoles is extending battery life; if this is achieved, it will enable continuous data collection for prolonged periods without requiring frequent recharging. To improve it, the focus on data storage constraints should be associated with the previous obstacle. The insoles should be able to stream data directly to the cloud during data collection [3]. In another study, some solutions were presented to improve these kinds of devices. An ideal smart insole includes a low-power consumption or self-sustainable system and presents biocompatibility [1]. For example, the most prominent issue in OpenGo and F-Scan models is their limited battery life, which allows for continuous data collection for only approximately two hours. As many wireless smart insoles require a connection to a device, such as a smartphone or PC, for data storage, some insoles, like OpenGo, can save data locally and transfer it later. However, they face the limitation of a determined local memory space, making continuous data collection difficult [3]. To solve this problem, AI algorithms can actively optimize the power consumption of wearable sensors. This can be achieved by reducing the amount of data transmitted and stored, as well as improving the efficiency of the algorithms that process the data [41].

Another significant concern in smart insole development is the need for a comprehensive and diverse dataset. For instance, to achieve 'high-accuracy' results, it is crucial to ensure that experiments are conducted in fully controlled environments and that subjects perform activities according to proper instructions. However, a significant issue is the limited number of subjects and their diversity. If all the above conditions are met, the ML models may be overfit to achieve high performance due to the limited data. On the other hand, when these models are applied to new subjects in uncontrolled environments such as daily life, accuracy may decrease abruptly [2]. To overcome this, simulating real-life scenarios in labs for semi-controlled and uncontrolled trials could be a valuable solution [2]. Therefore, it is essential to evaluate the effectiveness of a technique when deployed in a population that has not yet been validated. It is wrong to assume that a model trained and tested on impaired participants will have identical results as the same model trained and tested on healthy participants [37]. Gathering data from different regions, countries, industries, and activities to improve the accuracy, effectiveness, and robustness of models in smart insole applications is crucial for increasing the size and diversity of datasets [3]. However, if there is insufficient information, data augmentation can generate more data to overcome size limitations in the database without the need for additional experiments [2].

As smart insoles advance toward real-time monitoring and AI-driven analysis, ethical and data privacy concerns must be carefully considered. Continuous tracking of gait patterns, plantar pressure, and related biomechanical data constitutes sensitive personal information that can reveal health status, physical conditions, or behavioral patterns. Therefore, ensuring informed consent, transparency in data usage, and secure data transmission and storage is essential. Compliance with data protection regulations should be a baseline

requirement in both research and commercial applications. Furthermore, future developments should explore privacy-preserving techniques, such as on-device processing, data anonymization, and federated learning, to minimize the risks associated with centralized data collection. Addressing these challenges proactively will help ensure the responsible and ethical deployment of AI-powered smart insole systems across clinical, occupational, and personal settings.

As previously stated, and supported by the references in this document, the integration of ML techniques holds significant potential to revolutionize wearable technology, particularly in smart insole devices. Fazio et al. [1] confirmed in their study the existence of an algorithm that automatically detects the sensor's position and calibrates it to achieve the best output. However, the deployment of many of these techniques is hindered by hardware limitations. Therefore, further research and investigation are necessary to explore other techniques, develop models that integrate multiple modalities, and determine their application and performance [3]. Another crucial aspect is the creation and application of specific subject models. This method suggests that current regression models may learn person-specific patterns rather than broader occurrences. This likely results from the small sample sizes used for model training in many of the reviewed studies [37]. Future work should emphasize the development of open-source algorithms that are validated in clinically impaired populations. This will likely enhance estimation performance, ensuring confidence in predictions and decisions, while reducing barriers and gaining trust from both medical professionals and patients [41]. Open-sourcing subject-general models will also allow the interest and integration of diverse professionals from other fields of study in a multidisciplinary research team. Open-source data, as well as open-source code, in future studies would help accelerate the development of these techniques [37].

Other aspects must be addressed and suggested to develop an ideal device as already explored by the research team [39]: (1) the possibility of manufacturing an invisible and comfortable insole with a thin, textile, and soft design, with high durability, bio-degradable material and appropriate to most applications; (2) user-friendliness with the integration of a more straightforward software and compatible with other devices; (3) availability for the everyday user, offering a reliable and low-cost device; (4) ability to provide analysis in real time with a proper time response; (5) using an adequate number of sensors with consideration of battery life; (6) a database with different feet (size number, type, and pathology) and the ability to analyze instantly and provide the position of each sensor; (7) selection of the best type of sensors with higher precision, efficiency, and durability and assembling it according to the application(s); (8) giving the user the possibility to remove and reuse the sensors in other shoe insole sizes.

6. Conclusions

Integrating AI, specifically using ML techniques and algorithms, in smart insole prototypes has shown promising results, significantly improving performance, reliability, and accuracy. This is concluded based on the results, both experimental (offline) and in real-time contexts, presented in the different works that were considered for this investigation. This systematic review provides a comprehensive overview of current methodologies, identifying key trends and future directions for research. The importance of continued innovation and rigorous testing cannot be overstated. It is these efforts that are essential to fully realize the potential of AI-driven smart insoles, which capture different biomechanical data crucial to enhancing foot health and overall well-being.

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Abbreviations

The following abbreviations are used in this manuscript:

AI	Artificial Intelligence
AML	Action Manifold Learning
ANT	Adaptive Network Topology
BLE	Bluetooth Low Energy
BN	Bayes Net
CAN	Controller Area Network
CDC	Capacitance-to-Digital Converter
CNT	Carbon Nanotube
CoP	Center of Pressure
DAQ	Data Acquisition (Board)
DIC	Digital Image Correlation
DT	Decision Tree
EMG	Electromyography
EVA	Ethylene–Vinyl Acetate
FSR	Force Sensing Resistor
GB	Gradient Boosting
GPS	Global Positioning System
GRF	Ground Reaction Forces
HSPA	High-Speed Packet Access
HW	Hammerstein–Wiener
IBK	Instance-Based Learner
IMU	Inertial Measurement Unit
K-NN	k-Nearest Neighbors
LDA	Linear Discriminant Analysis
Li-Po	Lithium Polymer
LSTM	Long Short-Term Memory
LTE	Long-Term Evolution
MCU	Microcontroller Unit
MEMS	Micro-Electromechanical Sensors
ML	Machine Learning
MTB	Microcontroller Tactile Board
MUX	Multiplexer
NB	Naive Bayes
NB-IoT	Narrowband Internet of Things
NFC	Near-Field Communication
NN	Nearest Neighbor
NNs	Neural Networks
PC	Personal Computer
PCB	Printed Circuit Board
PDMS	Polydimethylsiloxane

PETG	Poly(ethylene terephthalate)-glycol
PETG + CF	Poly(ethylene terephthalate)-glycol with Carbon Fibers
PETG + KF	Poly(ethylene terephthalate)-glycol with Aramid Fiber
PEVA	Ethylene-Vinyl Acetate Copolymer
PLA	Poly(lactic) Acid
PVC	Polyvinyl Chloride
RF	Random Forest
RGB	Red–green–blue
RNN	Recurrent Neural Networks
SITUG	Smart Insole Timed Up and Go (system)
SMO	Sequential Minimal Optimization
STAMPS	Strain Analysis and Mapping of the Plantar Surface
SVM	Support Vector Machine
TENG	Triboelectric Nanogenerators
TPU	Thermoplastic Polyurethane

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