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Review of artificial intelligence in smart wearable devices under internet of things communication

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ABSTRACT

This paper aims to provide a review about the role of artificial intelligence (AI) in wearable devices, specifically smartwatches, fitness trackers, smart clothes, and smart eyewear. Machine learning (ML) and deep learning (DL) play essential roles in the development of these devices, thanks to their advanced algorithms with the support of the internet of things (IoT) framework. AI functionalities and metrology are detailed in these wearables, highlighting the use of convolutional neural networks (CNN) and recurrent neural networks (RNN) for applications such as activity recognition, health monitoring, and personalized recommendations. The paper demonstrates the AI implementation in smart devices, including stress detection by heart rate variability (HRV), personalizing fitness recommendations, muscle activity monitoring, and real-time image recognition. Challenges and potential solutions are discussed for a deep comprehension of the AI development in wearable devices.

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1. INTRODUCTION

The integration of artificial intelligence (AI) [1]–[3] like machine learning (ML) [4], [5] and deep learning (DL) [6], [7] with wearable technology: smartwatches, fitness trackers, smart clothes, and smart eyewear has brought about a new era of innovation and functionality in this fast-changing field. Wearable gadgets, smoothly incorporated into our daily routines, play a crucial role in tracking our health, improving our efficiency, and enriching our engagement with the environment. Within the context of internet of things (IoT) connectivity, networked nodes exchange data and insights to offer users tailored and contextually relevant experiences.

Smartwatches [8], [9] have evolved from simple accessories to advanced computer devices with many sensors [10] and functions. ML and DL algorithms in smartwatches measure fundamental data such as steps and calories while offering in-depth insights about the wearer's health and behavior. These devices use advanced analytics to provide users with valuable information about their health, such as heart rate variability (HRV) and sleep patterns, enabling them to make informed decisions about their well-being. Fitness trackers [11], similar to smartwatches but with a specific emphasis on health and exercise, utilize ML and DL methods to precisely identify and categorize physical activity. This type of device analyses data from onboard sensors like accelerometers and gyroscopes [12] to differentiate between activities such as walking, running, cycling, and swimming. They offer users comprehensive summaries of their workouts and their advancement towards fitness objectives. ML algorithms allow trackers to adjust to individual tastes and behaviors, providing individualized recommendations to enhance workout routines and improve outcomes

[13]. Smart clothes [14], [15], such as smart socks, smart pants, and smart shirts, are created by incorporating sensors [16] and actuators into clothing to function as wearable devices for tracking vital signs, posture, and environmental variables. ML algorithms are essential for analyzing the data gathered by sensors in smart clothing to offer immediate feedback on correcting posture, monitoring muscle activity, and ensuring thermal comfort [17]. DL methods allow these clothes to learn and adjust to the wearer's actions and preferences, providing personalized experiences designed for particular requirements [18]. Smart eyewear [19] is the cutting-edge form of wearable technology that provides augmented reality (AR) [20] experiences, hands-free communication, and individualized help in different situations. ML and DL algorithms enable functionalities like gesture detection, enabling users to operate gadgets and engage with virtual interfaces using natural gestures [21]. Furthermore, these algorithms allow smart eyewear to process visual data instantly, improving awareness of the situation and offering pertinent contextual information about the user's environment.

Central to the functionality of these wearable devices is their ability to communicate and exchange data within the broader IoT ecosystem [22], [23]. Through wireless connectivity standards such as Bluetooth, Wi-Fi, and cellular networks, smartwatches, fitness trackers, smart clothes, and smart eyewear can synchronize data with companion apps, cloud-based platforms, and other connected devices. ML and DL algorithms optimize data transmission and processing, ensuring timely delivery of insights and minimizing latency for a seamless user experience.

In essence, the integration of ML and DL in smartwatches, fitness trackers, smart clothes, and smart eyewear under the umbrella of IoT communication represents a convergence of cutting-edge technologies aimed at enhancing human capabilities and well-being. The device performance with AI can be evaluated with specific metrologies. As these devices continue to evolve and innovate, driven by advances in AI and connectivity, they hold the promise of transforming how we monitor our health, interact with technology, and experience the world around us.

Overall, this research provides the following contributions to the scientific research as follows:

i) This article explores the innovative fusion of AI, which encompasses ML and DL, with wearable technologies. This convergence marks the beginning of a new period of innovation, in which smartwatches, fitness trackers, smart garments, and smart eyeglasses not only improve our daily lives but also revolutionize how we interact with the environment.
ii) This overview provides the working principle, model implementation, and structure of AI in wearable devices. This article explores the transformative capabilities of AI-powered wearables, such as smartwatches with advanced data analytics that assist in making informed decisions about well-being and fitness trackers that provide personalized workout recommendations.
iii) We explore the cutting-edge smart clothing that adapts to the user body's needs, ensuring comfort and improving posture, and the futuristic smart eyewear that brings AR into everyday use, enhancing situational awareness and interaction through natural gestures. The key factor behind these progressions is the robust IoT ecosystem that facilitates immediate data sharing, enhancing the effectiveness and agility of these devices.
iv) This comprehensive examination not only highlights the latest technological innovations but also provides insights into the future trajectory of wearable technology. With the ongoing advancements in AI and connectivity, these intelligent devices hold the potential to revolutionize health monitoring, technological engagement, and our general perception of the world.

The paper is organized as follows: section 1 is about the growth statistic of the considering AI wearable device. Section 2 describes about the ML/DL methods and metrology in these smart wearable devices. Section 3 are about the practical analysis with case study and real-world application with IoT. Then, section 4 will discuss data privacy and security. Finally, in section 5, challenges, solutions, and future directions are analyzed appropriately, accompanied by conclusions at the end.

2. GROWTH STATISTIC OF SMART WEARABLE DEVICES

The worldwide market for wearable AI was estimated at USD 21.2 billion in 2022 and it is projected to increase at a compound annual growth rate (CAGR) of 29.8% from 2023 to 2030 [24]. The growing number of AI-enabled smart wearables is related to the advancement of IoT, with the wireless technology's incorporation. This section analyzes the growth of smart wearable devices and demonstrates the important roles in statistics.

2.1. Smartwatches

Smartwatches accomplished a high revenue share of over 30.2% in 2022 due to the rising awareness and concern among consumers regarding people's health. Moreover, it is projected to increase at a profitable pace during the forecasted timeframe as a result of the growing significance of interconnected devices in diverse sectors and the escalating demand for a connected environment. In 2022, North America had the highest market share of 27.2% in terms of revenue because of the investments made by private companies and the support of government programs to promote the use of AI technology [24]. According to Canalys research [25], there will be a significant increase in smartwatch shipments in emerging regions, particularly in the Middle East and Central and Eastern Europe, with a projected growth rate of 27 and 22% respectively, in 2024. Practically, the integration of AI into watches has brought a significant evolution of this device consumption demand, as reported in Tables 1 and 2.

Table 1. Worldwide wearable band shipment: forecast and annual growth

Category	2022 shipments (million)	2023 shipments (million)	2024 shipments (million)	Annual growth 2022/2023 (%)	Annual growth 2023/2024 (%)
Basic band	40.0	35.8	33.0	-10	-8
Basic watch	65.4	79.7	88.5	+22	+11
Smartwatch	77.5	70.7	82.7	-9	+17
Total	182.8	186.1	204.2	+2	+10

Table 2. Worldwide wearable band shipment: category share

Category	2022 shipments (%)	2023 shipments (%)	2024 shipments (%)
Basic band	22	19	16
Basic watch	36	43	43
Smartwatch	42	38	40
Total	100	100	100

2.2. Fitness trackers

In 2023, the global fitness tracker market was valued at USD 53.94 billion. It is expected to increase from USD 62.03 billion in 2024 to USD 290.85 billion by 2032, with a CAGR of 21.3% during the forecast period (2024 to 2032) [26]. Fitness trackers have gained significant popularity and are now widely accessible to the general public. These devices are utilized for the purpose of tracking and monitoring physical and fitness activities, including but not limited to the number of steps taken, calories burned and ingested, heart rate, distance traveled, duration of sleep, and breathing patterns. Wireless tracking devices can be synchronized with a computer or smartphone, allowing anyone to monitor fitness and health data from any location. According to Rizzo [27], there are more than 445 million wearable fitness devices, which were shipped to consumers, with fitness tracker revenue growing more than 31% due to the pandemic in 2020. Based on the report of Fortune Business Insights [26], the dramatic increase in fitness tracker market growth is illustrated in Figure 1.

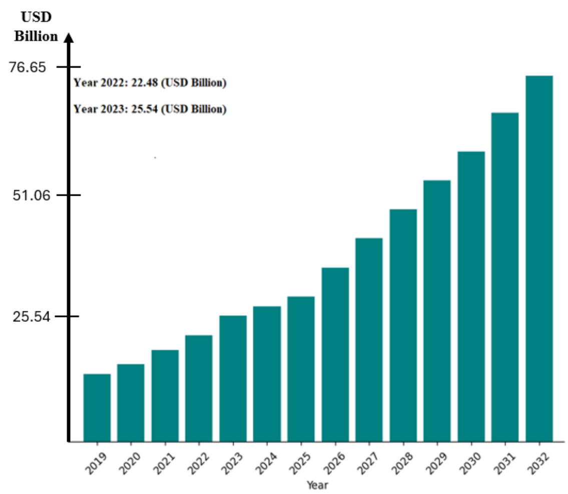

Figure 1. North America fitness tracker market size (USD billion)

2.3. Smart clothes

According to Grand View Research [28], the estimated size of the global smart clothing market in 2022 was USD 2.98 billion, and it is projected to experience a CAGR of 27.4% from 2023 to 2030. The market is undergoing substantial expansion, including in the sports and healthcare industries, due to the rising consciousness of health and fitness in everyday life. Smart clothing provides a variety of functions, such as biometric monitoring, recording physical activity, and improving performance. These functions allow users to keep track of their health indicators, optimize their exercise routines, and improve their general well-being. The increasing popularity of smart clothing is being driven by a cultural emphasis on a healthy lifestyle and a growing inclination towards real-time health monitoring. Market size value in 2023 was approximately USD 3.94 billion, and revenue forecast in 2030 was USD 21.48 billion, as shown in Figure 2.

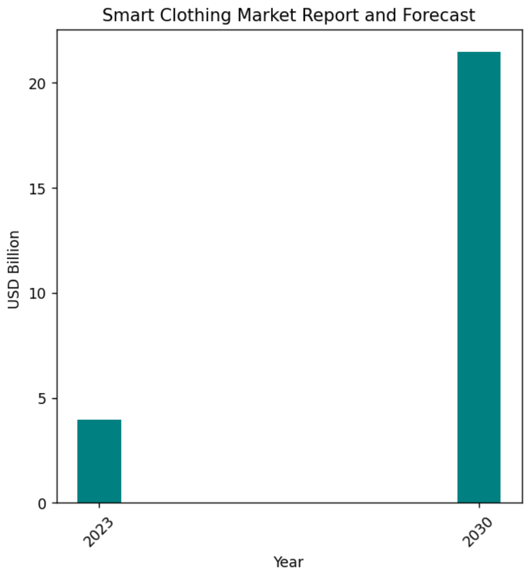

Figure 2. Smart clothing market data

2.4. Smart eyewear

In 2022, the global smart glasses market was valued at USD 1,232 million. Its CAGR has been about 27.1% from 2023 to 2030 [29]. Smart eyewear has risen in demand because of its capacity to carry out intricate computer-driven functions. Furthermore, the increasing popularity of wearable technology, combined with ongoing technical improvements, is anticipated to drive the expansion of the smart glasses market even more. Smart glasses market size value in 2023 was approximately USD 1,530.0 million, and revenue forecast in 2030 was USD 8,187.1 million, as shown in Figure 3.

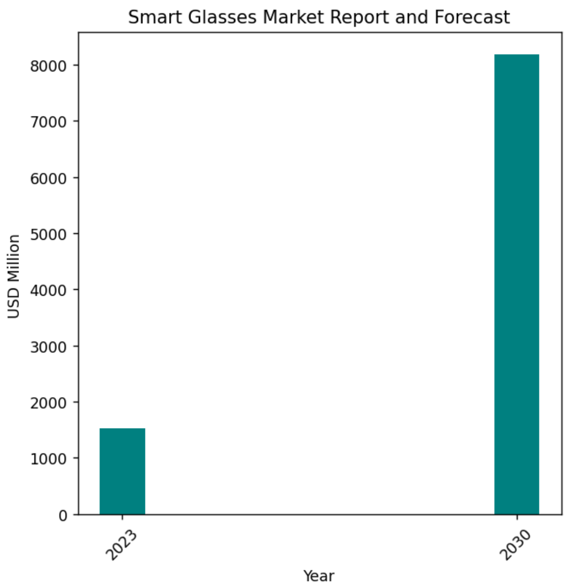

Figure 3. Smart eyewear market data

3. AI METHODS IN WEARABLE DEVICES

Smartwatches, fitness trackers, smart clothes, and smart eyewear have been successfully developed thanks to the high advanced technology of ML and DL. These wearable devices are now capable of offering highly personalized and accurate health and fitness insights, transforming the way we monitor our well-being and engage with technology. The synergy between wearable devices and cutting-edge ML and DL technologies has ushered in a new era of personalized health monitoring, proactive healthcare management, and enhanced human-computer interaction.

3.1. Smartwatches

ML algorithms process data from accelerometers [30], gyroscopes, and other sensors [31] to identify physical activities such as walking, jogging, cycling, or swimming. These algorithms often utilize techniques like supervised learning, where a labelled dataset is used to train classifiers such as support vector machines (SVM) [32], decision trees [33], and random forests [34] to recognize different activity patterns based on features extracted from sensor data. For instance, accelerometer data might be transformed using techniques such as Fourier transform or wavelet transform to extract time-frequency features, which are then used by the classifier. DL models enhance the precision of activity recognition in varied and changing settings by extracting intricate patterns from unprocessed data [35]. Convolutional neural networks (CNN) [36] and recurrent neural networks (RNN) [37], including long short-term memory (LSTM) network [38], are particularly effective here. CNN can automatically learn spatial hierarchies of features from raw sensor data (e.g., multi-dimensional time-series data from accelerometers and gyroscopes), while RNN, particularly LSTM and gated recurrent units (GRUs) [39], excel in capturing temporal dependencies and sequences in the data.

Smartwatches with heart rate monitors utilize ML techniques to evaluate heart rate data to provide insights on stress levels, recuperation, and cardiovascular health [40]. Techniques such as K-means clustering [41] can be used to segment heart rate data into different states (e.g., resting, moderate activity, and high activity) based on data acquisition method [42]. Additionally, hidden Markov models (HMMs) [43] can model the sequential nature of HRV over time to infer underlying physiological states. DL models, particularly those involving autoencoders and attention mechanisms, can evaluate intricate characteristics from HRV data [44]–[46], offering an in-depth understanding of physiological conditions and potential health concerns. Autoencoders can learn a compressed representation of HRV data, identifying subtle anomalies indicative of health issues. Attention mechanisms within sequence models (like transformers) can focus on critical time points in the HRV data, improving the accuracy of health assessments.

3.2. Fitness trackers

In fitness trackers, CNN is highly proficient at identifying complicated patterns in raw sensor data, leading to improved accuracy in recognizing activities even in challenging situations. Furthermore, calorie expenditure estimation can be improved by utilizing ML algorithms that combine activity data with user-specific characteristics like age, weight, and heart rate. DL algorithms can discern intricate connections between sensor inputs and energy expenditure, resulting in more accurate calorie burn predictions customized for each user. In performance optimization, ML algorithms can assess past activity data to suggest customized workout programs based on specific fitness objectives, preferences, and abilities. DL models can detect relationships between various sorts of workouts, aiding users in achieving a well-rounded and efficient training routine. Injury prevention is also included in the ML function, which identifies trends in biomechanical data from physical activities that suggest poor form or a higher risk of injury.

RNN, including variants like LSTM network, offers real-time feedback and coaching to assist users in maintaining good technique and minimizing the risk of injury. CNN can process spatial data from wearables to identify incorrect movement patterns, while LSTMs can model temporal dependencies to monitor changes over time. These models adapt to evolving user preferences and requirements by learning from historical data and user feedback, enhancing the user experience with personalized recommendations. Moreover, advanced DL architectures like transformers [47] and graph neural networks (GNNs) [48] are being explored for their potential to model complex interactions in biomechanical data and provide more sophisticated injury prevention insights.

3.3. Smart clothes

Smart clothing embedded with sensors can monitor vital signs such as heart rate, respiration rate, and body temperature. ML algorithms study this data to detect patterns and abnormalities, giving users real-time insights into their health status [49]. ML algorithms also support posture analysis, which processes data from motion sensors embedded in smart clothing to analyze posture and movement patterns. This feature helps users to maintain proper posture, prevent musculoskeletal injuries, and improve overall body mechanics.

Decision tree algorithm [50] is utilized in smart clothes to analyze sensor data patterns and detect anomalies like fall detection in movement or posture, alerting users to potential injury risks or incorrect exercise techniques. DL examines biomechanical data to offer insights on form, technique, and the most effective training approaches. In rehabilitation and injury prevention, ML algorithms evaluate movement data collected by smart clothes to aid in rehabilitation activities and reduce the risk of injuries. DL identifies slight variations in motion patterns that suggest possible risks of harm, allowing individuals to take preventive actions to reduce those risks. In addition, smart clothing incorporates sensors to monitor ambient conditions, including temperature, humidity, and ultraviolet radiation levels. ML algorithms explore the data to offer customized suggestions, such as modifying clothing layers or using sunscreen according to the user's surroundings.

3.4. Smart eyewear

ML algorithms process visual input from smart eyewear cameras to identify objects, text, landmarks, and faces in visual recognition and AR. This feature allows for functionalities like instantaneous translation, description of surroundings, and identification of faces. SVM is applied in smart eyewear for tasks such as hand gesture recognition or emotion detection from facial expressions, enabling intuitive interactions with wearable devices and enhancing communication experiences.

AR applications involve DL models such as generative adversarial networks (GAN) [51] that analyze camera feeds and superimpose digital information onto the user's field of view, enhancing AR experiences. This method encompasses virtual navigation signals, contextual details about the environment, and interactive overlays for gaming and entertainment. Moreover, the smart glass system can also assist blind and visually impaired individuals using computer vision techniques [52], DL models, audio feedback, and tactile graphics to help them navigate independently in low-light conditions [53].

3.5. AI metrology in smart devices

Metrology in ML and DL for smart wearables in IoT communication [54]–[64] focuses on measuring and evaluating the performance, accuracy, reliability, and efficiency of these devices' ML/DL models.

i) In data quality and acquisition, ensuring data quality and dependability is the initial step in the metrology process for data gathered by wearables. The measuring parameters include data accuracy, precision, sampling rate, and signal-to-noise ratio. Additionally, it is crucial to evaluate the accuracy of sensor data and identify any biases or artifacts that may have been introduced during data collection.
ii) Feature extraction is essential in ML/DL applications as it converts raw sensor data into relevant input features for the models. Metrology assesses the efficiency of feature extraction methods in acquiring pertinent data while reducing redundancy and noise. Feature selection approaches are evaluated to measure their influence on model accuracy and computational speed.
iii) Metrology in model creation involves training, validating, and optimizing the model. The performance of ML/DL models is evaluated using key measures like accuracy, precision, recall, F1-score [63]–[65], and area under the curve (AUC) [66]. Model interpretability, scalability, and robustness to environmental fluctuations must be evaluated in several IoT communication scenarios. Additionally, considerations such as model interpretability, scalability, and robustness to environmental variations are assessed under different IoT communication scenarios.
iv) Smart wearables operate under limited power and computational resources. Thus, metrology involves measuring the energy consumption and resource utilization of ML/DL algorithms to ensure optimal performance while minimizing power consumption. Model quantization, compression, and sparsity optimization are evaluated to balance accuracy and energy efficiency.
v) Real-time inference and latency are crucial in IoT applications, particularly in activity recognition, health monitoring, and gesture recognition. Metrology monitors the latency and throughput of ML/DL models running on smart wearable devices. Methods including model trimming, hardware acceleration, and edge computing are evaluated to fulfill real-time needs while preserving accuracy.

4. CHALLENGES AND POTENTIAL SOLUTIONS

4.1. Challenges

The current state of AI in wearable devices highlights significant advancements and potential, but there are still various challenges [67]–[70]. Wearable devices generate vast amounts of data, including physical activity, heart rate, and sleep patterns, which are processed within the IoT ecosystem. However, ensuring high-quality data collection while managing power consumption presents a significant challenge. Real-time data processing is further complicated by the constraints of limited battery life and computational power in wearable devices. Additionally, interoperability remains a concern, as different manufacturers utilize various protocols, making seamless integration difficult without universal standards. Data transmission to the cloud introduces latency, which is particularly problematic for time-sensitive applications. Edge computing can mitigate this issue, but it demands powerful on-device processing capabilities. Moreover, DL models such as CNNs and RNNs require substantial computational power, which wearables may struggle to support due to their size and battery limitations. The variability and noise in sensor data [71]–[73] can complicate AI training, making high-quality and sufficient data crucial for effective model performance. Optimizing AI models for wearables involves techniques like model pruning, quantization, and knowledge distillation, which help reduce model size and complexity while maintaining efficiency and accuracy.

4.2. Solutions

In smart wearable devices, AI integration requires the appropriate approach and process to make the implemented models optimally effective [74]–[79]. Several solutions and proposals can be considered to address challenges in wearable device data processing and AI implementation. Optimized data collection strategies, such as sensor fusion techniques, can help reduce power consumption while maintaining data accuracy by utilizing low-power sensors for continuous monitoring and activating higher-power sensors only when necessary. Real-time processing can be improved through lightweight algorithms designed to minimize computational load, while edge computing enables local data preprocessing, reducing latency and conserving battery life. Interoperability issues can be mitigated by advocating standardized protocols and APIs across manufacturers, promoting industry collaboration to establish universal communication standards. To address latency, edge computing capabilities should be leveraged for local data processing and inference, deploying lightweight ML models optimized for real-time responsiveness. Computational resource constraints in wearable devices can be managed by developing and optimizing DL models specifically for these environments, incorporating techniques like model compression, pruning, quantization, and knowledge distillation to reduce size and complexity while maintaining performance. Ensuring high-quality and sufficient training data requires robust preprocessing techniques, including noise reduction and data augmentation, to improve consistency and reliability. Finally, advanced model optimization techniques are essential for enhancing efficiency without compromising accuracy, with continuous refinement focused on reducing computational overhead and energy consumption.

5. CONCLUSION

This study has explained the vital significance of AI in wearable technology, focusing on smartwatches, fitness trackers, smart clothes, and smart eyewear. ML and DL algorithms have significantly advanced these devices, supported by the IoT framework. The diverse uses of AI in wearable technology have been emphasized, demonstrating its significant influence on user experience and functioning. Furthermore, the article has emphasized the crucial importance of AI in protecting user privacy and data security in the wearable technology environment. The growing integration of these devices into our everyday routines highlights the critical necessity for robust AI-driven systems to safeguard sensitive data. In addition to privacy and security, AI enhances the personalization and adaptability of wearable devices, tailoring functionalities to individual user needs and preferences. For instance, AI-driven analytics can provide users with customized health insights, proactive health monitoring, and early detection of potential medical conditions. This personalized approach improves user engagement and contributes to overall well-being by promoting healthier lifestyles and informed decision-making. Moreover, AI's evolution in wearable technology drives innovation in other fields, such as AR and smart healthcare solutions. Wearables equipped with AI capabilities are becoming integral in professional sectors, including sports, medicine, and occupational safety, by providing real-time data and feedback that enhance performance, aid in diagnosis, and ensure safety. As technology advances, interdisciplinary collaboration among AI researchers, wearable technology developers, and regulatory bodies will be essential. Establishing clear guidelines and ethical standards will be crucial to addressing data ownership, consent, and transparency challenges. These measures will foster trust among users and ensure that the benefits of AI in wearable technology are realized responsibly and sustainably. In conclusion, the dynamic interplay between AI and wearable technology is reshaping the landscape of personal and professional domains. The continuous advancement in AI algorithms and IoT integration promises a future where wearables enhance convenience and lifestyle and play a pivotal role in maintaining health and security. The commitment to innovation, ethical practices, and user-centric design will determine the trajectory of this transformative field, ultimately enriching the human experience through intelligent and secure wearable solutions.

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This journal uses the Contributor Roles Taxonomy (CRediT) to recognize individual author contributions, reduce authorship disputes, and facilitate collaboration.

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Guido Matrella						✓		✓		✓				
Paolo Ciampolini						✓				✓				✓

C : **C**onceptualization
M : **M**ethodology
So : **So**ftware
Va : **Va**lidation
Fo : **Fo**rmal analysis
I : **I**nvestigation
R : **R**esources
D : **D**ata Curation
O : Writing - **O**riginal Draft
E : Writing - Review & **E**diting
Vi : **Vi**sualization
Su : **Su**pervision
P : **P**roject administration
Fu : **Fu**nding acquisition

CONFLICT OF INTEREST STATEMENT

Authors state no conflict of interest.

DATA AVAILABILITY

The data that support the findings of this study are available from the corresponding author [MLH], upon reasonable request.

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