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A Standards-Based Review of Wearable and loT Technologies in Parkinson's Telemedicine

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Abstract:

Objective: To identify and categorize existing standards relevant to wearable and IoT technologies in Parkinson's Disease telemedicine. This review focuses on secure, interoperable data exchange and integration into clinical workflows. It also aims to highlight literature gaps and real-world applications of these standards.

Materials and Method: A four-step structured review was conducted, including a PubMed search that retrieved 233 publications using Boolean logic. Large language models were used to filter and cluster 50 key articles into four standardization domains. Additional technical documents expanded the final corpus to 63 sources for comprehensive thematic analysis.

Results: Among the 63 reviewed sources, four major thematic areas were identified, including standards for communication, implementation, security, and collaborative development. Notably, security and clinical integration standards were underrepresented, prompting the manual addition of 13 relevant studies, with IEEE/UL 2933 and USCDI emerging as key frameworks supporting secure data transmission and interoperability in Parkinson's disease (PD) telemedicine. Communication standards such as IEEE 11073 and HL7 FHIR demonstrated strong potential for integrating wearable sensor data into EHR systems, improving data reliability and clinical decision-making. Collaborative initiatives like the WAMIII project have accelerated the development and validation of PD-specific digital biomarkers through cross-sector partnerships. Overall, the adoption of interoperable, secure, and standardized frameworks is essential for realizing the full clinical utility of wearable technologies in PD care.

Discussion: Despite the promise of interoperability standards like IEEE/UL 2933, USCDI, IEEE 11073, and HL7 FHIR, real-world adoption remains hindered by technical, economic, and workflow-related barriers. Inconsistent implementation by device manufacturers and poor alignment with clinical routines often result in fragmented systems and limited data integration. Collaborative initiatives like WAMIII have advanced standardization for motor symptoms in Parkinson's disease but still face challenges in non-motor assessments and adaptability to new technologies. Addressing these limitations will require deeper collaboration between industry and clinicians, patient-centered design approaches, and large-scale validation studies. Ultimately, the success of telemedicine in Parkinson's care depends on embedding secure, flexible, and clinically compatible standards into routine practice.

Conclusion: This review highlights the essential role of interoperability and security standards—such as HL7 FHIR, Continua Guidelines, and IEEE/UL 2933—in enabling effective data integration for Parkinson's telemedicine. Advancing remote monitoring will require stronger adherence to these standards, large-scale clinical validation, and sustained collaboration across healthcare, industry, and regulatory stakeholders.

Background and Significance

Parkinson's Disease (PD) is a progressive neurodegenerative disorder affecting movement control, with symptoms such as tremor, rigidity, and bradykinesia. Globally, over 10 million individuals are living with PD[1]. The prevalence of PD has doubled in the past 25 years, with projections indicating a continued increase, particularly in aging populations[2].

Effective management of PD requires continuous monitoring to assess symptom progression and treatment efficacy. Traditional clinical assessments are often limited to periodic evaluations, which may not capture the fluctuating nature of PD symptoms. In recent years, wearable and Internet of Things (IoT) technologies have emerged as promising tools for real-time, remote monitoring of PD symptoms. These devices can track various motor symptoms, including tremor, bradykinesia, and gait disturbances, providing valuable data for clinicians and researchers[3] .

Despite the potential benefits, integrating wearable and IoT devices into PD management presents several challenges. Data security and privacy are primary concerns, as these devices collect sensitive health information that must be protected against unauthorized access and breaches[4]. Additionally, interoperability issues arise due to the lack of standardized protocols for data exchange between devices and healthcare systems, hindering seamless integration into electronic health records[5]. Addressing these challenges is critical to fully leverage the capabilities of wearable and IoT technologies in PD care.

Standardization efforts are underway to establish guidelines for the design, implementation, and integration of wearable medical devices. For instance, the International Telecommunication Union’s H.810 Continua Design Guidelines provide a framework for ensuring interoperability and security in personal connected health systems[6]. Furthermore, initiatives like the Wearable Medical Applications Interoperability and Intelligence (WAMIII) aim to build consensus on global certification systems that assure patient security and privacy in the use of wireless connected medical devices[7]. These efforts are essential to facilitate the widespread adoption of wearable technologies in clinical practice.

Objective

This review aims to identify and categorize existing standards pertinent to wearable and IoT technologies utilized in Parkinson's telemedicine. Specifically, the objectives are to:

1. Examine the scope and application of current standards supporting secure, interoperable data exchange.
2. Identify gaps in the literature regarding security and clinical integration.
3. Illustrate the practical application of these standards through real-world examples of Parkinson's monitoring tools.

Materials and Methods

A structured, four-step methodology was employed to conduct this review as shown in Figure 1:

1. A comprehensive landscape analysis was conducted to identify interoperability and security standards pertinent to the use of wearable and IoT devices in Parkinson's Disease (PD) care. This analysis was guided by established clinical and informatics frameworks to ensure relevance and applicability.
2. An advanced Boolean search was executed on PubMed, utilizing controlled vocabulary and keywords related to PD, telemedicine, and health data standards. This search yielded 233 relevant publications.
3. Large language models (LLMs) were employed to filter and cluster the retrieved publications, resulting in a focused subset of 50 key articles. These articles were then categorized into four thematic groups based on their alignment with existing standardization frameworks.
4. To address underrepresented categories, particularly Security and Clinical Integration, additional use cases and technical documentation were incorporated, expanding the final corpus to 63 sources.

The identified standards were organized into four domains:

1. Security and Clinical Integration Standards: Including IEEE/UL 2933, which provides a framework for Trust, Identity, Privacy, Protection, Safety, and Security (TIPPSS) in clinical IoT data and device interoperability .
2. Communication and Data Exchange Standards: For example, the ISO/IEEE 11073 Personal Health Device (PHD) Standards, which define common protocols for interoperability between personal health devices and managers, facilitating seamless data exchange .
3. Collaborative Development Programs: Such as the Wearable Medical Applications Interoperability and Intelligence (WAMIII), which focuses on advancing interoperability in wearable medical devices.
4. Implementation Frameworks and Guidelines: Such as the Fast Healthcare Interoperability Resources (FHIR), which enables the electronic exchange of healthcare information

Results

Among the 63 reviewed sources, the distribution across thematic groups was as follows and the results shown in Table 1:

1. Communication and Data Exchange Standards: 14 publications
2. Implementation Frameworks and Guidelines: 13 publications
3. Security and Clinical Integration Standards: 14 publication
4. Collaborative Development Programs: 22 publications

Security and Clinical Integration Standards

This distribution reveals a significant underrepresentation of security-related standards in the literature, so we manually add 13 studies in the security area. Notably, IEEE/UL 2933 and the United States Core Data for Interoperability (USCDI) were the only identified standards addressing secure transmission and EHR interoperability[8]. A practical example of how security and interoperability standards can be applied in Parkinson's telemedicine is demonstrated through the Moticon SCIENCE Insole, a wearable sensor device designed for real-time gait monitoring[9]. This insole system is embedded with pressure and motion sensors that continuously capture data related to gait rhythm, weight distribution, and postural stability—parameters that are clinically relevant in detecting motor fluctuations in individuals with Parkinson's disease.

The secure transmission of this sensitive physiological data from the insole to mobile devices and subsequently to cloud platforms is supported by the IEEE/UL 2933 standard[10]. This framework provides specifications for Trust, Identity, Privacy, Protection, Safety, and Security (TIPPSS) in the Internet of Medical Things (IoMT)[11]. Specifically, IEEE/UL 2933 enables end-to-end encryption, device authentication, tamper detection, and audit logging, thereby mitigating risks of data interception, unauthorized access, or manipulation during home-based monitoring[12]. These protections are especially crucial when wearable devices operate beyond the confines of hospital networks, such as in remote care or assisted living environments.

IEEE/UL 2933 and USCDI provide a comprehensive pathway from secure data acquisition to clinical decision support as shown in Figure 2. Once securely transmitted, the wearable data must be integrated into clinical systems in a structured and actionable format. The USCDI plays a pivotal role. USCDI defines standardized health data classes that can be populated with output from devices like the Moticon insole. For example, gait rhythm variability can be mapped to the "Functional Status" field within an electronic health record (EHR), while device-specific metadata can populate "Device Identifier" entries. This structured representation enables longitudinal tracking of patient outcomes, supports reimbursement through remote patient monitoring (RPM) codes, and ensures that sensor-derived metrics are clinically interpretable by providers[13].

Communication and Data Exchange Standards

Communication and data exchange standards are critical infrastructure for the implementation of telemedicine and wearable devices in Parkinson's disease (PD) management. The IEEE 11073 Personal Health Device (PHD) family of standards provides a comprehensive framework that enables interoperability between a wide range of medical devices and healthcare information systems. These standards are particularly applicable to PD applications because they focus on continuous monitoring capabilities and standardized representation of movement-related parameters.

Some studies showed that when applied to PD monitoring, the IEEE 11073 standard facilitates consistent data exchange by standardizing syntactic and semantic aspects of communication, ensuring that tremor measurements, gait parameters, and other movement metrics maintain their clinical significance across different platforms and devices[14]. Their study showed that successful implementation can reduce integration costs while improving data reliability for clinical decision making in PD care.

IEEE 11073 Service-Oriented Device Connectivity (SDC) extends these capabilities described it as "manufacturer-independent interoperability," which is critical for complex PD monitoring scenarios that may involve multiple devices from different vendors[15]. Their study highlights how SDC enables plug-and-play integration of medical devices while maintaining tight synchronization between different measurement modalities, which is critical for correlating various PD symptoms with physiological parameters.

For PD-specific applications, some studies found that these standards must address unique transmission considerations, including appropriate sampling frequencies for different symptoms (ranging from 20 Hz for bradykinesia assessment to 100 Hz for fine tremor detection), as well as optimized data representation to balance clinical fidelity and bandwidth limitations[16]. Their study showed that clinical utility improves when the transmission protocol incorporates adaptive sampling based on the severity of the detected symptoms.

The implementation of these standards in PD monitoring further benefits from a structured metadata handling approach. Some studies showed that contextual information (e.g., medication timing, activity classification, and environmental factors) significantly enhances the interpretability of motor data when using a standardized format[17]. Their study validated methods for using HL7 FHIR resources to represent PD-specific observations while maintaining interoperability with electronic health record systems.

The security of these standards is particularly important for PD applications. Some studies evaluated cryptographic requirements within the IEEE 11073 framework and found that while these standards provide secure transmission mechanisms, PD-specific implementations must carefully consider the computational overhead of security measures, especially for wearable devices with limited processing power[18]. Their study recommended energy-efficient cryptographic methods that are both HIPAA-compliant and do not significantly affect battery life in long-term monitoring scenarios.

Collaborative Development Programs

The Wearables and Medical IoT Interoperability and Intelligence (WAMIII) project is an important collaborative initiative to address interoperability challenges in telehealth applications for Parkinson's disease. Some studies have established cross-industry partnerships to develop consensus-based connectivity solutions specifically addressing the unique needs of movement disorder monitoring[19]. The WAMIII framework has facilitated the collaborative development of technical standards for Parkinson's disease-specific metrics, and some studies highlight how these collaborations have resulted in validated digital biomarkers for key Parkinson's disease symptoms and consistency across a variety of sensor technologies[20]. And there are some studies further demonstrating how collaborations between academic institutions, technology companies, and healthcare providers, under the auspices of WAMIII, have accelerated clinical implementation through shared testing methods and reference implementations, particularly for home monitoring systems that capture the fluctuating characteristics of complex Parkinson's disease symptoms[21]. These collaborative efforts have been instrumental in addressing the challenges argued that the main barriers to widespread adoption of remote PD monitoring are: fragmented technical approaches and lack of standardized outcome measures that can be reliably compared across different monitoring platforms and clinical settings[22].

Implementation Frameworks and Guidelines

The Continua Design Guidelines, created by the Continua Health Alliance (now part of the Personal Connected Health Alliance), lay out a solid framework to make sure the data from wearable devices is secure, consistent, and reliable. These guidelines outline specific protocols for how devices should talk to each other, making it easier for

personal health tools and clinical systems to exchange information smoothly. According to some studies, sticking to these guidelines boosts the reliability of the data we get, which is important for effective remote monitoring[23, 24]. When it comes to managing Parkinson's disease, having a standardized approach means we can accurately capture and communicate changes in motor performance and other critical signs, enabling timely clinical interventions and smarter treatment choices.

At the same time, HL7 FHIR has become a key player in healthcare data exchange. This standard defines a set of modular "resources" and application programming interfaces (APIs) that allow different health information systems to communicate effortlessly. With FHIR, data from wearable devices can be easily integrated into electronic health records (EHRs), ensuring clinicians have up-to-date and comprehensive patient information. Some studies display how FHIR makes quick data integration possible, which is important for keeping tabs on disease progression and timely adjustments to therapies[25, 26].

Despite the potential of these standards, there are still challenges to overcome in getting wearable device data widely adopted for Parkinson's disease management. Wearable sensors can provide constant, high-quality data, but the lack of a universal standard across different platforms and devices often leads to disjointed data streams. Some studies pointed out that while current studies show how useful these devices can be, the absence of standardized protocols often limits how effectively we can use the collected data in clinical settings[27]. It emphasizes the urgent need for more research into developing thorough frameworks that fully incorporate both the Continua Design Guidelines and HL7 FHIR standards.

In terms of the technical aspects, integrating these standards into clinical practice carries huge influence for patient care. When data from wearable devices is accurately and securely transferred into EHR systems, it paves the way for a more personalized treatment approach. Continuous monitoring can lead to the early detection of symptoms worsening, allowing providers to adjust their interventions based on real-time insights. As a result, patient outcomes can improve, and the overall efficiency of healthcare delivery is enhanced. The benefits of this strategy are clear, with a growing amount of research emphasizing the positive impact of standardized data exchange on remote patient monitoring[23-27].

Discussion

In the *Results* section, we present the functional roles of these standards and support our findings with literature and real-world case examples. And in this section, this study further explores the current limitations and challenges associated with the implementation of these standards.

Security and Clinical Integration Standards

While standards like IEEE/UL 2933 and the USCDI provide comprehensive frameworks for secure data exchange and interoperability in healthcare, their adoption in commercial and clinical settings faces several significant challenges.

One primary barrier is the inconsistent adherence by medical device manufacturers to these standards. Implementing IEEE/UL 2933, which emphasizes principles of Trust, Identity, Privacy, Protection, Safety, and Security (TIPPSS), requires substantial investment in redesigning device architectures and ensuring rigorous security measures. Some manufacturers may be hesitant to undertake these changes due to the associated costs and complexities, leading to a fragmented landscape where not all devices meet the same security and interoperability benchmarks[28, 29]. This inconsistency hampers the seamless integration of devices into clinical workflows and poses potential risks to patient data security[30].

Integrating standardized data exchange protocols into existing clinical workflows presents another significant challenge. Clinical environments are complex, and workflows are often tailored to specific practices or institutional protocols. The introduction of new standards necessitates changes in these workflows, which can be met with resistance from healthcare providers accustomed to established routines[31]. Additionally, if the standards are not

designed with a deep understanding of clinical operations, they may introduce inefficiencies or require additional steps that burden healthcare professionals, ultimately impeding adoption[32].

A notable example illustrating these challenges occurred at Cedars-Sinai Medical Center in Los Angeles[33]. In 2002, the hospital attempted to implement a new Computerized Physician Order Entry (CPOE) system. However, the system faced significant resistance from physicians due to its time-consuming nature and the inflexibility of its alerts and reminders. The lack of adequate physician input during the system's development and insufficient prior testing led to a failed implementation, highlighting the critical importance of aligning new technologies with clinical workflows and securing end-user buy-in[34].

To overcome these obstacles, a collaborative approach is essential. Manufacturers should engage with healthcare providers during the design phase to ensure that devices not only comply with standards like IEEE/UL 2933 but also align with the practical needs of clinical settings. EHR vendors must work towards enhancing system capabilities to support USCDI data elements, facilitating seamless data integration. Furthermore, involving clinicians in the development and implementation process can help tailor solutions that fit naturally into existing workflows, thereby promoting acceptance and effective utilization.

Communication and Data Exchange Standards

The IEEE 11073 family of standards faces significant implementation challenges for Parkinson's disease (PD) monitoring. While these standards provide a comprehensive interoperability framework, they struggle to meet the broad technical requirements of PD symptoms, ranging from 20 Hz sampling for bradykinesia to 100 Hz sampling for tremor detection[16]. Security implementation poses additional challenges, as the computational demands of encryption can put pressure on wearable devices with limited capacity, forcing them to compromise between data security and usability[18]. Although comprehensive frameworks such as IEEE/UL 2933 emphasize key security and privacy principles, commercial adoption remains inconsistent and manufacturers are reluctant to invest in implementing these standards. Furthermore, integrating these standardized protocols into existing clinical workflows is often resisted by healthcare providers who are accustomed to established routines, especially when these standards lack a good understanding of clinical practice.

Collaborative Development Programs

While the WAMIII program has successfully fostered cross-sector collaboration, significant gaps remain in achieving standardization of outcome measures for all aspects of Parkinson's disease monitoring. Motor symptom assessments have been successfully standardized[21], but comparable progress has been lacking for non-motor symptoms and cognitive aspects of Parkinson's disease. Despite coordinated efforts, fragmentation in technical approaches continues to impede widespread clinical adoption[22]. Future collaborative development should focus on three key areas: addressing the unique temporal requirements of Parkinson's disease monitoring, where medication timing and symptom fluctuations are closely aligned; expanding patient-driven design in the standardization process to ensure that standards address the lived experience of Parkinson's disease management; and developing an adaptable framework to incorporate emerging technologies without requiring a complete redesign of the system. Effective implementation will require collaboration between manufacturers and healthcare providers during the design phase to ensure that solutions not only meet technical standards, but also meet clinical needs.

Implementation Frameworks and Guidelines

As we look ahead, it's clear that connecting new wearable technologies with our current healthcare systems will take a strong team effort from all device makers, clinical researchers, and regulatory groups. Future studies should focus on large-scale clinical trials to see how effective these integrated telemedicine systems are.

Plus, working together to create compatible interoperability protocols will be important to breaking down current obstacles and making sure we fully gain the advantages of telemedicine for managing Parkinson's disease. Incorporating wearable devices into telemedicine platforms for Parkinson's disease depends on successfully following interoperability standards. These frameworks help keep data secure, consistent, and easily available,

allowing for more timely and personalized care. As the research shows, using these standards not only promotes remote monitoring but also sets the stage for better patient outcomes and more efficient healthcare delivery.

Limitation

This study has several limitations that should be considered when interpreting the findings. First, although the literature search was conducted systematically using Boolean logic on PubMed, the search was limited to a single database and English-language publications, which may have excluded relevant studies from other databases or non-English sources.

Second, the use of large language models (LLMs) for relevance filtering and topic clustering—while innovative—introduces an element of algorithmic bias. The performance of LLMs depends heavily on training data and prompt design. As such, certain nuanced but relevant papers may have been inadvertently excluded due to semantic mismatch or insufficient keyword representation in abstracts.

Third, although the standards we selected were identified as the core criteria for data exchange in clinical integration, they were evaluated in this study primarily based on theoretical applicability and documentation rather than actual deployment data. Empirical validation through case studies or clinical trials is limited, and practical implementation of these standards remains underreported in the current literature.

Finally, while this review included 63 publications, the small number of articles addressing security and interoperability in clinical settings highlights a broader gap in the literature. This underrepresentation may have limited the depth of analysis in one of the most critical domains for the success of wearable technologies in Parkinson's telemedicine.

Future work should include a broader database search strategy, multi-language inclusion, expert validation of LLM outputs, and direct engagement with device manufacturers and healthcare institutions to assess on-the-ground adoption of these standards.

Conclusion

In conclusion, this review demonstrates that established standards such as the Continua Design Guidelines, HL7 FHIR, and IEEE/UL 2933 play a critical role in facilitating secure and interoperable data exchange between wearable devices and clinical systems for Parkinson's telemedicine. The integration of these frameworks promises to enhance real-time monitoring and improve the personalization of therapeutic interventions, thereby supporting better clinical outcomes. However, several challenges persist, including inconsistent adherence to these standards by manufacturers and the fragmented nature of cross-platform data integration. Moreover, the scarcity of empirical validation studies highlights a significant gap between theoretical frameworks and their practical deployment in clinical settings. The current landscape calls for more collaborative research efforts that include multi-stakeholder partnerships among device manufacturers, clinicians, and regulatory bodies.

Future work should focus on large-scale clinical trials and real-world case studies to assess the efficacy and robustness of these standards in everyday practice. By addressing these challenges, the healthcare community can move closer to establishing a fully integrated telemedicine environment that effectively leverages wearable and IoT technologies. Overall, a unified approach to standardization will be key to advancing remote patient monitoring and enhancing the overall efficiency of Parkinson's disease management.

Appendix

Figure 1. PRISMA Flow Diagram for Study Selection

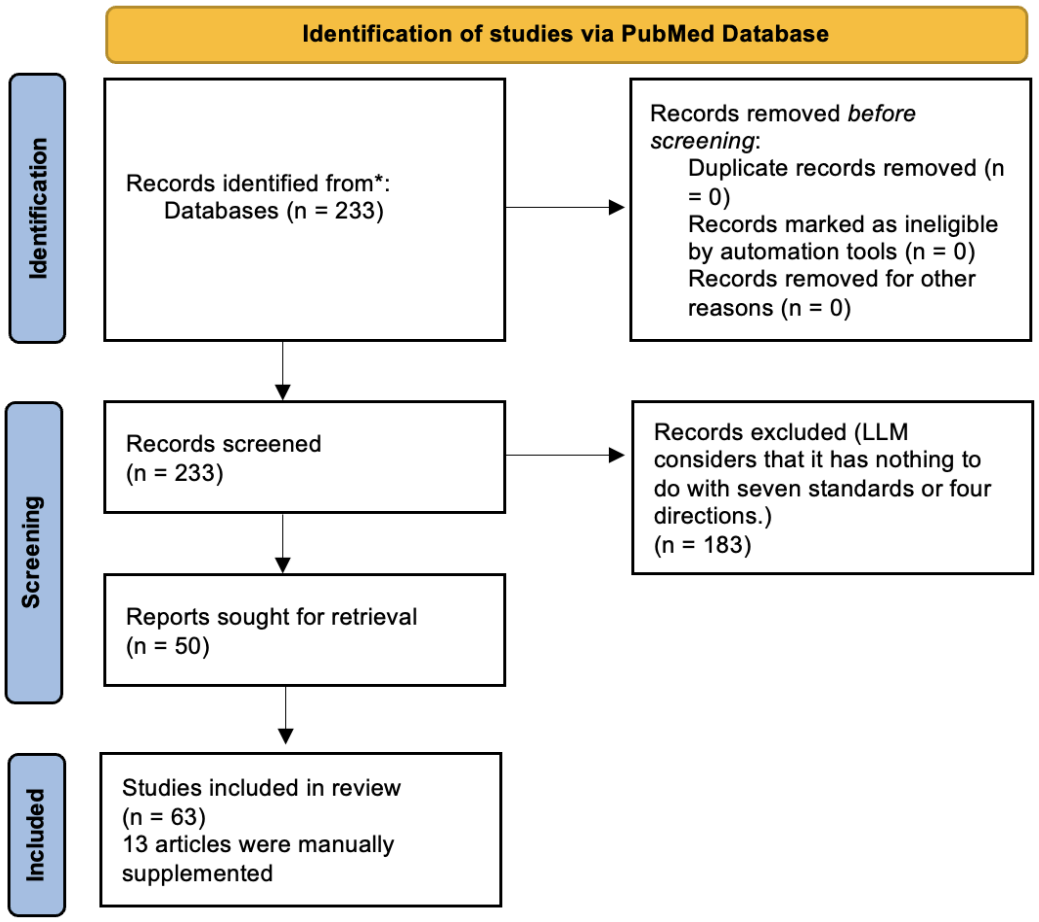

Figure 2. Security and Clinical Integration Standards

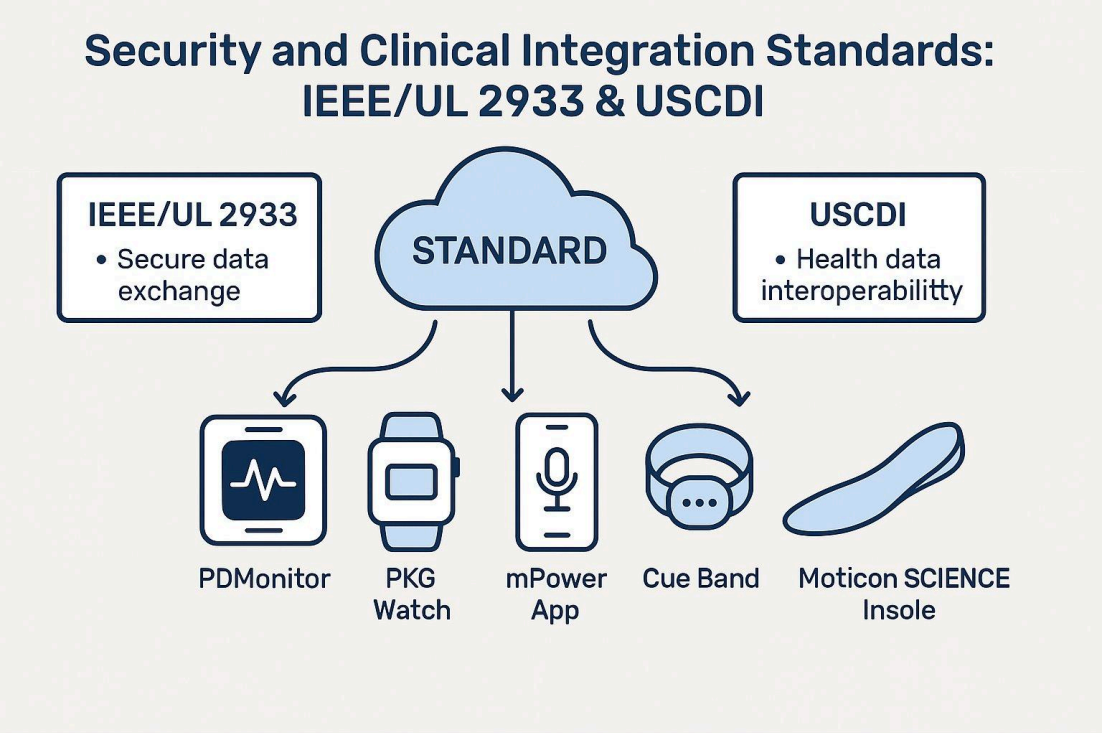

Figure 3. WAMIII Program: Bridging Stakeholders in PD Monitoring

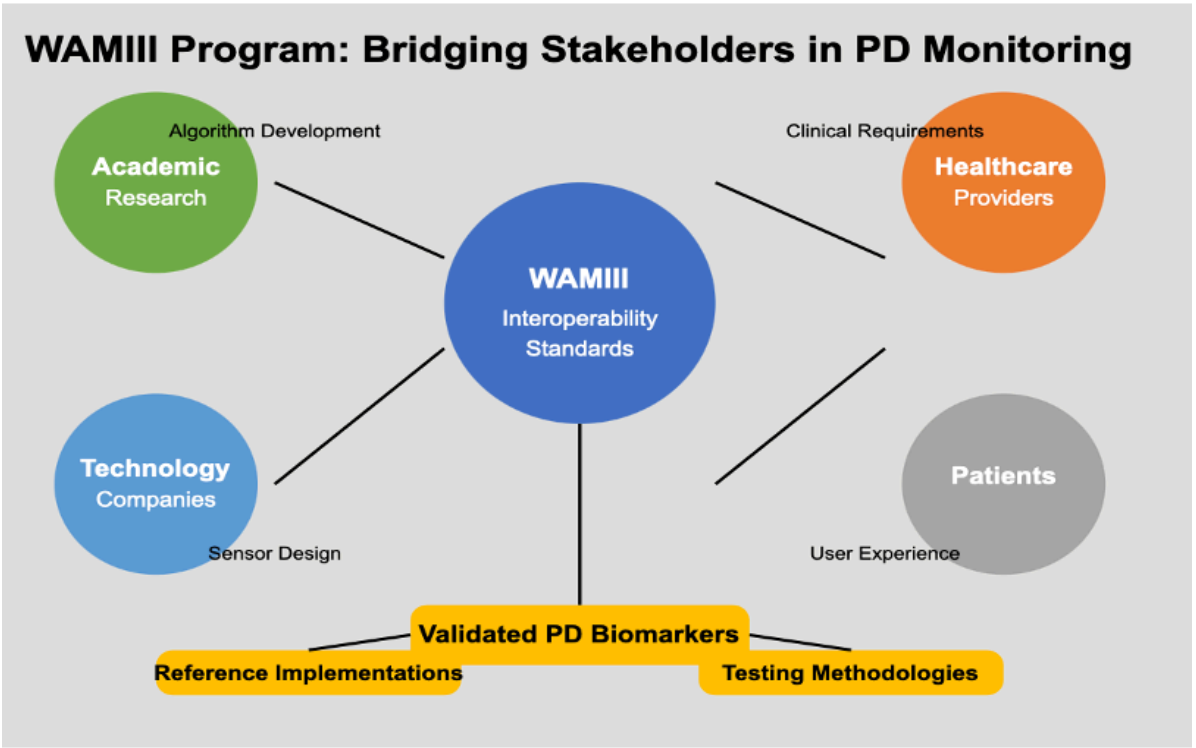

Table 1. Articles selected for full-text review

	Article	Subject
1	Li et al. (2024)	Collaborative Development Program
2	Amprimo et al. (2024)	Collaborative Development Program
3	MejiaCruz et al. (2024)	Collaborative Development Program
4	Battista et al. (2023)	Collaborative Development Program
5	Chen et al. (2023)	Collaborative Development Program
6	Guo et al. (2022)	Collaborative Development Program
7	Kostovich et al. (2022)	Collaborative Development Program
8	Tsanas et al. (2021)	Collaborative Development Program
9	Ibrahim et al. (2020)	Collaborative Development Program
10	Viswanathan et al. (2020)	Collaborative Development Program
11	O'Day et al. (2020)	Collaborative Development Program
12	LeMoyne et al. (2020)	Collaborative Development Program
13	Channa et al. (2020)	Collaborative Development Program
14	Rehman et al. (2020)	Collaborative Development Program
15	Refai et al. (2018)	Collaborative Development Program
16	Nguyen et al. (2017)	Collaborative Development Program
17	Rovini et al. (2017)	Collaborative Development Program
18	Pasluosta et al. (2015)	Collaborative Development Program
19	Cancela et al. (2011)	Collaborative Development Program
20	Bachlin et al. (2009)	Collaborative Development Program
21	Patel et al. (2007)	Collaborative Development Program
22	Bonato et al. (2004)	Collaborative Development Program
23	Hadley et al. (2024)	Communication and Data Exchange Standards
24	Boege et al. (2024)	Communication and Data Exchange Standards
25	Sun et al. (2023)	Communication and Data Exchange Standards
26	Ricci et al. (2022)	Communication and Data Exchange Standards
27	Huo et al. (2020)	Communication and Data Exchange Standards
28	Teshuva et al. (2019)	Communication and Data Exchange Standards
29	Pastorino et al. (2013)	Communication and Data Exchange Standards
30	Hoffman et al. (2011)	Communication and Data Exchange Standards
31	Patel et al. (2011)	Communication and Data Exchange Standards
32	Cancela et al. (2010)	Communication and Data Exchange Standards
33	Patel et al. (2010)	Communication and Data Exchange Standards
34	Bonato P. et al. (2009)	Communication and Data Exchange Standards
35	Giansanti et al. (2008)	Communication and Data Exchange Standards
36	Tamura et al. (2006)	Communication and Data Exchange Standards
37	Amprimo et al. (2024)	Implementation Frameworks and Guidelines
38	Dousty et al. (2023)	Implementation Frameworks and Guidelines
39	Nouriani et al. (2023)	Implementation Frameworks and Guidelines

	Article	Subject
40	Li et al. (2023)	Implementation Frameworks and Guidelines
41	Liu et al. (2022)	Implementation Frameworks and Guidelines
42	Deb et al. (2022)	Implementation Frameworks and Guidelines
43	Chén et al. (2020)	Implementation Frameworks and Guidelines
44	An et al. (2020)	Implementation Frameworks and Guidelines
45	Pardoel et al. (2020)	Implementation Frameworks and Guidelines
46	Lauraitis et al. (2019)	Implementation Frameworks and Guidelines
47	Hssayeni et al. (2019)	Implementation Frameworks and Guidelines
48	Lin et al. (2017)	Implementation Frameworks and Guidelines
49	Hssayeni et al. (2016)	Implementation Frameworks and Guidelines
50	Mazumder et al. (2019)	Security and Clinical Integration Standards
51	Bloem et al. (2020)	Security and Clinical Integration Standards
52	Oertel et al. (2020)	Security and Clinical Integration Standards
53	Stew et al. (2007)	Security and Clinical Integration Standards
54	Critical Path Institute. et al. (2025)	Security and Clinical Integration Standards
55	Michael et al. (2024)	Security and Clinical Integration Standards
56	Alberts et al. (2023)	Security and Clinical Integration Standards
57	Parkinson’s Foundation. et al. (2023)	Security and Clinical Integration Standards
58	Espay et al. (2020)	Security and Clinical Integration Standards
59	Geerlings et al. (2024)	Security and Clinical Integration Standards
60	Critical Path Institute. et al. (2023)	Security and Clinical Integration Standards
61	Klucken et al. (2018)	Security and Clinical Integration Standards
62	Visser et al. (2016)	Security and Clinical Integration Standards
63	Beck et al. (2017)	Security and Clinical Integration Standards

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