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Leveraging Artificial Intelligence and Wearable Technologies in Glucose Management: A Comprehensive Scoping Review of Current Trends and Future Directions

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Abstract—The integration of artificial intelligence (AI) and machine learning (ML) with wearable health monitoring systems presents transformative opportunities for advancing diabetes management. This paper delivers an in-depth review of state-of-the-art AI/ML methodologies applied to wearable sensor technology, focusing on noninvasive techniques for real- time blood glucose monitoring. In particular, we investigate the utility of wrist-worn photoplethysmography (PPG) signals for blood glucose estimation and assess IoT-enabled continuous glucose monitoring (CGM) systems. A systematic literature search was conducted across prominent databases such as IEEE Xplore, PubMed, Scopus, and Web of Science. Studies were meticulously selected based on stringent criteria including technological innovation, methodological rigor, and clinical relevance. Our synthesis reveals significant progress in the accuracy, computational efficiency, and practical deployment of AI/ML algorithms in diabetes monitoring, while also identifying persistent challenges related to signal noise reduction, data heterogeneity, and sensor integration. The review further discusses the potential of these advanced technologies to enable early diagnosis, facilitate personalized treatment strategies, and ultimately improve patient outcomes. These insights underscore the critical need for continued interdisciplinary research and collaboration to overcome existing l imitations and to drive the successful translation of these innovations into clinical practice.
Keywords—Artificial intelligence, machine learning, wearable health monitoring, diabetes management, photoplethysmography, continuous glucose monitoring, Internet of Things, predictive analytics, noninvasive devices

INTRODUCTION

Background and Rationale

Diabetes mellitus is recognized as one of the most significant global health challenges of the 21st century. Recent estimates by the International Diabetes Federation [1] indicate that over 537 million adults are currently living with diabetes—a figure projected to rise to more than 600 million by 2030. In parallel, the World Health Organization [2] has highlighted diabetes as a leading cause of morbidity and premature mortality worldwide. The disease imposes an enormous clinical burden due to its chronic nature and the severe complications it precipitates, such as cardiovascular diseases, neuropathy, retinopathy, and nephropathy [3][4]. Economically, diabetes contributes billions of dollars annually to healthcare costs and indirectly affects national economies through lost productivity and disability.The rapid evolution of wearable sensor technology over the past decade has significantly altered the landscape of chronic disease management, particularly for diabetes. Early wearable devices were primarily designed for basic physiological monitoring, such as tracking heart rate or step count. However, recent innovations have led to the development of sophisticated systems capable of continuous, real-time monitoring of multiple biomarkers. For example, continuous glucose monitoring (CGM) devices such as the Dexcom G6 and FreeStyle Libre provide minimally invasive, real-time data on glucose levels, enabling better glycemic control [5]. These advancements are underpinned by innovations in microelectronics, sensor miniaturization, and wireless data transmission [6]. Moreover, the integration of additional sensors to monitor parameters like heart rate variability and physical activity supports a holistic approach to managing diabetes and its comorbidities.In parallel, artificial intelligence (AI) and machine learning (ML) have catalyzed a paradigm shift in predictive analytics and personalized medicine. AI/ML algorithms— including deep neural networks, support vector machines, and ensemble learning methods—have been applied to analyze complex datasets generated by wearable sensors. These algorithms show promise in predicting blood glucose fluctuations and detecting hypoglycemic events, thus enabling proactive intervention strategies [7][8]. However, challenges such as data sparsity, variability in sensor accuracy, and the need for real-time processing hinder the seamless integration of AI/ML in clinical settings [9].]Given the convergence of biomedical engineering, computer science, and clinical medicine in addressing diabetes management, a comprehensive scoping review is warranted. Such a review is essential to synthesize emerging research trends, identify methodological gaps, and propose future directions that bridge the gap between experimental innovations and their practical clinical applications [10].

A.Research Problem and Gap

Despite significant advancements in AI/ML, a substantial gap remains between these technological innovations and their practical application in wearable, sensor-driven diabetes monitoring– systems. While AI/ML models have contextualize the reliability and robustness of included studies.

- **Data Synthesis and Analysis:** The study employed both narrative and thematic synthesis methods. Narrative synthesis provided a descriptive literature overview, while thematic analysis—assisted by qualitative data coding in NVivo—identified trends, key themes, and research gaps. Visual representations, including tables, charts, and network maps, were utilized to enhance clarity.

This protocol serves as a structured framework, ensuring methodological rigor, reproducibility, and transparency in the review process.

A. ligibility Criteria

The eligibility criteria were developed using the Population, Concept, and Context (PCC) framework to ensure rigor, relevance, and completeness. The inclusion and exclusion criteria were carefully designed to capture high- quality research focusing on the integration of Artificial Intelligence (AI) and Machine Learning (ML) with wearable health monitoring technologies for diabetes management.

1) Inclusion Criteria: Studies will be included if they meet the following conditions:

Study Types

- Primary Research Studies

– Experimental Studies: Randomized Controlled Trials (RCTs), Cohort Studies, and Case-Control Studies evaluating AI/ML applications in wearable diabetes monitoring.

– Observational Studies: Cross-sectional studies, pilot studies, and feasibility studies ~~providing~~ provide real-world insights.

– Proof-of-Concept Studies: Research demonstrating innovative AI/ML applications in wearable diabetes monitoring, even if clinical validation is pending.

- Secondary Research Studies

– Systematic reviews, meta-analyses, and scoping reviews synthesizing findings on AI/ML applications.

- Conference Proceedings

– Peer-reviewed conference papers from high-impact AI, ML, and healthcare informatics conferences (e.g., IEEE, ACM, NeurIPS, AAAI, MEDINFO).

- Industry Reports & Grey Literature

– Reports from government agencies, professional organizations, and industry white papers discussing AI-powered wearable diabetes management.

Population

- Studies focusing on human participants diagnosed with Type 1 or Type 2 diabetes or those at high risk of developing diabetes.
- No restrictions on age, gender, or ethnicity to ensure diverse representation.
- Studies including healthy control groups will be considered only if they provide insights into AI/ML model differentiation (e.g., comparing diabetic vs. non- diabetic sensor data).

Interventions & Technologies

Studies must involve wearable sensors for diabetes monitoring, integrated with AI/ML algorithms, including:

– Continuous Glucose Monitors (CGMs) (e.g., Dexcom, FreeStyle Libre)
– Smartwatches & Fitness Trackers (e.g., Apple Watch, Fitbit, Garmin)
– Smart Patches & Biosensors for glucose, heart rate, or sweat composition analysis
– Multi-Modal Systems combining multiple physiological signals (e.g., glucose + heart rate + activity)

The AI/ML component must be used for at least one of the following:

– Predicting glucose levels and identifying hypoglycemia/hyperglycemia risks
– Personalized insulin dosage recommendations
– Detecting anomalies in sensor data for improved accuracy
– Risk stratification and trend analysis using machine learning models

Study Outcomes

Studies must report at least one of the following:

– *AI/ML Model Performance:* Accuracy, sensitivity, specificity, AUC-ROC.
– *Clinical Utility:* Effectiveness in real-world diabetes management.

– *Data Quality Considerations:* Handling of missing or noisy wearable sensor data.
– *Implementation Challenges:* Barriers to AI/ML integration in wearable diabetes monitoring.
– *Future Research Directions:* Gaps and unexplored opportunities in AI/ML-driven wearable health monitoring.

Publication Characteristics

- **Timeframe:** Studies published in the last 10 years to capture recent AI/ML advancements.
- **Language:** Only English-language studies will be included due to feasibility constraints.

2)Exclusion Criteria: Studies will be excluded if they meet any of the following conditions:

Study Scope & Focus

- Research on wearable technology for general health tracking without diabetes-specific applications.
- AI/ML applications in diabetes that do not involve wearable sensor data (e.g., AI in electronic health records).
- Studies focusing solely on hardware development of sensors without AI/ML integration.

Methodological Limitations

- Studies lacking methodological transparency, prevent~~ing~~ reproducibility.
- Non-peer-reviewed sources, such as blog posts or editorial opinions.
- Duplicate publications or abstracts without sufficient primary data.

3)Justification for Eligibility Criteria : The selection criteria ensure the inclusion of high-quality, methodologically rigorous studies, offering a comprehensive synthesis of AI/ML-driven wearable sensor applications in diabetes management. To ensure study quality and minimize bias, the following risk of bias assessment tools will be applied:

- **Cochrane RoB2** – for Randomized Controlled Trials (RCTs).
- **ROBINS-I** – for observational studies.
- **AMSTAR 2** – for systematic reviews.

B. Information Sources

To ensure a comprehensive and methodologically rigorous review, a systematic search will be conducted across multiple electronic databases, grey literature sources, and reference lists of relevant studies. The selection of sources is based on their relevance to Artificial Intelligence (AI), Machine Learning (ML), biomedical engineering, and healthcare research.

1) Primary Databases : The following databases will be searched to capture high-quality, peer-reviewed studies:

- **IEEE Xplore:** A leading repository for AI/ML applications in healthcare, featuring research on wearable technologies and computational models.
- **PubMed:** A premier biomedical literature database, covering clinical applications of AI in diabetes management and digital health technologies.
- **Scopus:** A multidisciplinary database that includes high- impact journals relevant to AI/ML, wearable sensor technologies, and diabetes research.
- **Web of Science:** A robust indexing database ensuring comprehensive coverage of high-quality studies from healthcare, engineering, and AI disciplines.

2) Grey Literature Sources : To capture cutting-edge research and industry advancements, the following grey literature sources will be reviewed:

- **Google Scholar:** For non-indexed but high-impact conference papers and technical reports on AI-powered wearable health monitoring.
- **Preprint Servers:** arXiv, bioRxiv, and medRxiv will be searched for emerging AI/ML research before formal peer review.
- **Government & Regulatory Reports:** Publications from health organizations (e.g., WHO, FDA, ADA) discussing AI-driven diabetes monitoring standards.

3) Conference Proceedings : Conferences are critical sources for state-of-the-art AI/ML applications in wearable health monitoring. Peer-reviewed papers from the following conferences will be considered

- **IEEE International Conference on Biomedical and Health Informatics (BHI)**
- **International Conference on Artificial Intelligence in Medicine (AIME)**
- **NeurIPS (Neural Information Processing Systems)**
- **AAAI Conference on Artificial Intelligence**
- **MEDINFO (International Medical Informatics Association)**

4) Citation Chasing & Cross-Referencing : To maximize the comprehensiveness of the review, reference lists of included studies and recent systematic reviews will be manually screened for additional relevant literature. Citation chaining will be employed to identify key studies that may not have been retrieved in the initial database searches.

C. Search Strategy

A structured and reproducible search strategy will be developed in consultation with an information specialist. The search methodology will incorporate Medical Subject Headings (MeSH) terms (for PubMed), database-specific indexing terms, and Boolean operators to ensure comprehensive retrieval of relevant literature.

1) Search Query Development: The search strategy will include a combination of controlled vocabulary terms and free-text keywords. The following key concepts will be considered,

- **Population (Diabetes):** "Diabetes," "Diabetes Mellitus," "Type 1 Diabetes," "Type 2 Diabetes," "Blood Glucose Monitoring."
- **Intervention (Wearable Sensors):** "Wearable Sensors," "Wearable Devices," "Continuous Glucose Monitor," "Smartwatch," "Biosensors," "Noninvasive Monitoring."
- **AI/ML Applications:** "Artificial Intelligence," "Machine Learning," "Deep Learning," "Neural Networks," "Predictive Analytics," "Data-Driven Models."

An example Boolean search string for PubMed is:

("Diabetes Mellitus" OR "Diabetes" OR "Type 1 Diabetes" OR "Type 2 Diabetes") AND ("Wearable Sensors" OR "Continuous Glucose Monitor" OR "Smartwatch" OR "Biosensors") AND ("Artificial Intelligence" OR "Machine Learning" OR "Deep Learning" OR "Predictive Analytics").

The search string will be tailored for each database according to its specific indexing conventions to maximize retrieval efficiency.

2) Search Execution and Refinement: An initial test search will be conducted to evaluate the sensitivity and specificity of the search terms. Based on preliminary results, iterative refinements will be made to optimize precision while ensuring comprehensive coverage of relevant studies. Searches will be conducted independently by two reviewers to minimize bias, and a detailed search log will be maintained to document modifications, excluded terms, and rationale for refinements.

Study Selection Process

The study selection process will follow a systematic two- stage screening approach to ensure objectivity, minimize bias, and enhance reproducibility.

3) Stage 1: Title and Abstract Screening

Two independent reviewers will screen the titles and abstracts of all retrieved studies based on the predefined inclusion and exclusion criteria. The screening process will adhere to the following principles:

- If a study's relevance remains unclear based on the title and abstract alone, it will be retained for full-text screening to prevent premature exclusion.
- Discrepancies between reviewers will be resolved through discussion. If consensus cannot be reached, a third reviewer will be consulted to make the final decision.

4) Stage 2: Full-Text Review

Studies that pass the title and abstract screening will be retrieved in full text for further evaluation. The full-text review will be conducted as follows:

- Two independent reviewers will assess the full-text articles against the inclusion and exclusion criteria to ensure adherence to the eligibility framework.
- Studies failing to meet the eligibility criteria will be excluded, and the reason for exclusion will be systematically recorded to maintain transparency and reproducibility.
- A PRISMA (Preferred Reporting Items for Systematic Reviews and Meta-Analyses) flow diagram will be constructed to visually represent the study selection process, detailing the number of studies screened, included, and excluded at each stage.

D. Data Extraction and Charting

A structured data extraction form will be developed to systematically collect relevant information from the included studies. The extraction process will be piloted on a random subset of studies to ensure completeness, consistency, and reliability. This process will facilitate the synthesis of evidence on the integration of AI/ML with wearable health monitoring for diabetes management.

1) Data Fields for Extraction: The following key variables will be systematically extracted from each study:

- **Study Metadata:** Author(s), publication year, journal/conference, and digital object identifier (DOI).
- **Study Characteristics:** Study design (e.g., observational, experimental, systematic review), sample size, participant demographics, and inclusion/exclusion criteria.

- **Wearable Sensor Technology:** Type of sensors used (e.g., continuous glucose monitors (CGMs), accelerometers, photoplethysmography), data acquisition methods, sensor placement, and frequency of measurements.
- **AI/ML Methodology:** Types of AI/ML models employed (e.g., deep learning, reinforcement learning, support vector machines), feature selection techniques, preprocessing steps, and details of training/testing datasets.
- **Outcomes and Performance Metrics:** Model performance indicators, including accuracy, sensitivity, specificity, precision-recall, AUC-ROC scores, and interpretability of AI models.
- **Limitations and Bias Considerations:** Identified biases, data quality concerns (e.g., missing or noisy data), generalizability issues, and potential confounding factors reported in the studies.

2) Data Management and Software Tools: To ensure efficient and accurate data extraction, the following tools and procedures will be employed:

- **Software for Data Extraction:** Microsoft Excel will be used for structured data entry and quantitative analysis, while NVivo will assist in qualitative synthesis and thematic analysis.
- **Quality Control Measures:** Extracted data will undergo independent verification by a second reviewer to ensure accuracy and minimize errors.
- **Discrepancy Resolution:** Any inconsistencies in data extraction will be resolved through discussion between the reviewers. If necessary, a third reviewer will provide a final decision to ensure reliability.

E. Quality and Bias Assessment

Although scoping reviews do not traditionally require a formal risk of bias assessment, an adapted quality appraisal framework will be employed to enhance the contextual understanding of study reliability. This assessment will provide insights into the robustness of AI/ML applications in wearable diabetes monitoring.

1) Study Quality Indicators: Each included study will be evaluated based on the following key quality indicators:

- **Study Design Rigor:** Assessment of methodological clarity, appropriateness of study design, adequacy of sample size, and presence of control or comparison groups where applicable.
- **Transparency of AI/ML Models:** Evaluation of model explainability, reproducibility of methods, openness of source code or algorithms, and description of hyperparameter tuning strategies.
- **Data Quality and Integrity:** Examination of data completeness, accuracy, preprocessing techniques, and handling of missing or noisy data.
- **Generalizability and External Validity:** Analysis of whether study findings can be applied to broader populations, including consideration of demographic diversity and real-world applicability.
- **Potential Biases:** Identification of confounding factors, selection bias, reporting bias, and AI-related biases such as data imbalance or overfitting.

A structured appraisal table will be used to document the assessment results, ensuring transparency in the evaluation process.

2) Narrative Summary and Integration: A narrative synthesis of study quality will be presented in the results section, summarizing common strengths and limitations across the reviewed literature. Identified biases will be ritically discussed, particularly in relation to AI/ML performance, data representativeness, and clinical applicability.

F. Data Synthesis and Analysis

A comprehensive multi-method approach will be employed to synthesize findings from the included studies, combining qualitative and quantitative techniques to provide a holistic understanding of AI/ML applications in wearable diabetes monitoring.

1) Narrative Synthesis: A structured narrative synthesis will be conducted to identify and categorize key trends across the reviewed literature. Studies will be systematically grouped based on:

- **AI/ML Methodologies:** Supervised vs. unsupervised learning, deep learning architectures, ensemble learning techniques.
- **Wearable Sensor Types:** Continuous glucose monitors (CGMs), multi-modal biosensors, smartwatches with AI-driven health monitoring.
- **Study Designs and Clinical Contexts:** Experimental studies (e.g., RCTs, pilot studies) vs. observational studies, real-world vs. controlled settings.

The synthesis will highlight emerging trends, technical advancements, methodological limitations, and gaps in current research.

2) Thematic Analysis: A qualitative thematic analysis will be conducted using NVivo to identify recurring themes across

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studies. Key thematic categories will include:

- **AI Model Performance:** Accuracy, sensitivity, specificity, AUC-ROC, interpretability of models.
- **Clinical Impact and Usability:** Effectiveness in real-world diabetes management, patient adherence, integration into clinical workflows.
- **Challenges in Deployment:** Data quality issues, sensor reliability, regulatory and ethical considerations, bias in AI decision-making.

Interrelationships between these themes will be explored to assess the broader implications of AI-powered wearable diabetes monitoring.

3) Data Visualization and Quantitative Synthesis: To enhance interpretability and accessibility, findings will be presented through visual analytics, including:

- **PRISMA Flow Diagram:** A flowchart detailing the study selection process, including inclusion and exclusion at each screening stage.
- **Tabular Summaries:** Comparative tables outlining study characteristics, AI/ML techniques, wearable sensor modalities, and reported outcomes.
- **Performance Metrics Charts:** Bar plots and scatter plots illustrating model accuracy, sensitivity, and specificity across different studies.
- **Network Analysis and Cluster Mapping:** Graph- based visualizations to represent relationships between AI methodologies, wearable sensor types, and clinical applications.
- Where applicable, meta-analytic techniques may be applied to summarize quantitative results, provided sufficient homogeneity exists among included studies.

4) Integration of Findings: A synthesis matrix will be developed to integrate findings from the narrative synthesis, thematic analysis, and quantitative visualizations. This will provide a structured framework for identifying overarching trends, methodological best practices, and future research directions in AI-driven wearable diabetes monitoring.

RESULTS

A. Overview of Included Studies

This section provides a comprehensive summary of the key characteristics of the studies included in this review, offering a broad perspective on the literature landscape concerning AI/ML applications in diabetes monitoring, prediction, progression, and management.

1) Total Number of Studies: A total of **87 studies** were included in this review. The study selection process is illustrated using the **PRISMA flow diagram** (Figure 1), which details the number of studies screened, reasons for exclusion, and final inclusion criteria.

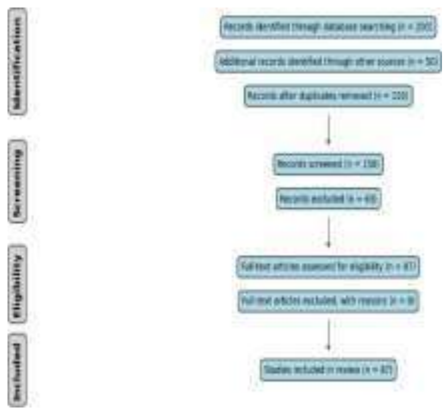

Fig. 1: PRISMA Flow Diagram illustrating the study selection process.

2) *Study Design Breakdown:* To systematically analyze the existing research on diabetes prediction using AI/ML, the reviewed studies were categorized into four primary study designs: Experimental Studies, Observational Studies, Review Articles, and Comparative & Benchmarking Studies. Table 1, summarizes the distribution of these study design

Study Design	Number of Studies (N)	Proportion (%)
Experimental Studies	59	67.8
Observational Studies	8	9.2
Review Articles	20	23.0
Comparative & Benchmarking Studies	5	5.7
Total	87	100

Table 1: Classification of Studies Based on Research Design

The breakdown of each study category is provided below:

a) *Experimental Studies:* Experimental studies constitute the largest category (67.8%), emphasizing the development, testing, and validation of AI/ML models for diabetes prediction and blood glucose monitoring. These studies involve novel algorithmic enhancements, non- invasive sensor integration, and predictive modeling techniques aimed at improving accuracy and usability in clinical and real-world settings. Notable contributions include:

- **Non-invasive Monitoring:** Several studies focus on non-invasive techniques such as wristband PPG-based glucose monitoring[69] IoT-based continuous glucose monitoring (CGM)[80]and PPG-based Type II diabetes prediction models[81].
- **AI/ML-based Predictive Modeling:** Advanced ML techniques have been explored, including novel loss functions for predictive modeling using clinical lab data[82] and machine learning-based pulse wave analysis for diabetes diagnosis[89].
- **Wearable and Sensor Data Integration:** The use of real-time data from wearable devices[70] is another critical aspect, enabling improved personalized monitoring and management.

b) *Observational Studies:* Observational studies (9.2%) primarily analyze real-world data to evaluate existing models and develop population-based screening frameworks. These studies do not involve direct interventions but leverage large-scale datasets to identify patterns and trends in diabetes onset and progression. Key contributions include:

- **Population Stratification:** Identification and classification of prediabetic individuals based on physiological and demographic data[78].
- **ECG-based Glucose Monitoring:** Utilization of electrocardiogram (ECG) signals for detecting diabetes and prediabetes[86], demonstrating an alternative to traditional invasive methods.

c) *Review Articles:* Review articles account for 23.0% of the surveyed studies, providing comprehensive evaluations of the current state-of-the-art in diabetes prediction and monitoring technologies. These papers synthesize findings from various experimental and observational studies to highlight key trends, limitations, and future directions. Major topics include:

- **Non-invasive Monitoring Surveys:** Systematic reviews analyzing non-invasive glucose monitoring technologies [53][54][58][59][60][65][66][67][88].
- **Wearable Technology in Diabetes Management:** Reviews focusing on the role of smart wearables in diabetes prediction and continuous moitoring[71][72][73][76]. *Comparative & Benchmarking Studies:* Comparative and benchmarking studies (5.7%) assess and compare the performance of different AI/ML models for diabetes prediction. These studies play a crucial role in evaluating model generalizability and effectiveness across multiple datasets and experimental conditions. Key contributions include:
- **Model Performance Comparisons:** Direct evaluation of traditional machine learning models (e.g., Decision Trees, SVM, Neural Networks) against newer deep learning-based approaches.
- **Validation Across Datasets:** Cross-validation studies ensuring the robustness of predictive models when applied to diverse populations and real-world clinical data.

To provide a visual representation of the study distribution, a pie chart is illustrated in Figure 2.

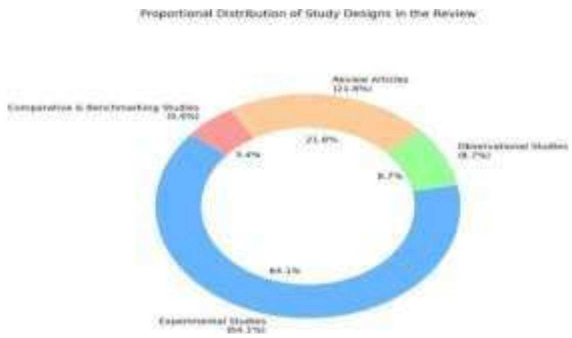

Fig. 2: Proportional distribution of study designs in the review

The majority of studies focus on experimental research, reflecting the growing emphasis on AI-driven innovations in diabetes prediction. However, the limited number of benchmarking studies highlights the need for more rigorous comparative analyses to ensure model reliability and reproducibility.

3) Sample Size and Demographics

The reviewed studies encompass a wide range of sample sizes and participant groups. Figure 3 summarizes the sample sizes and key demographic characteristics. The studies can be broadly categorized as follows:

a) Small-Scale and In-Silico Investigations: Some studies rely on established datasets or in-silico experiments,

- OhioT1DM dataset with 12 subjects [1][6].
- 6 subjects in [28] and 4 subjects in [30].
- A single Type II diabetes patient monitored over two months in [49]

b) Moderate to Large Cohorts and Aggregated Datasets: Other studies recruited moderate to large cohorts or combined multiple datasets:

- Cohorts include 21 participants [22], 200 subjects [23], 290 participants for PPG signal collection [24], and 451 Type I diabetes patients [17].
- Integrated datasets examples:

– A synthetic dataset with 7,691 instances combined with the PIMA Diabetes Dataset (768 instances) [27][34].
– Datasets with 768, 2,000, and 1,000 instances [29[39].
– A large cross-sectional study in China for diabetes screening with 10,794 participants (8,096 for training and 2,698 for validation) [74].

c) Specialized Cohorts and Wearable Studies: Several studies focused on specialized cohorts or wearable technology*:*

- An experimental study in Cuenca, Ecuador, with 217 participants (127 females, 90 males, ages 22–65) evaluated wristband PPG signals for non-invasive blood glucose estimation [69].
- A wearable device study involving 13 participants [70].
- An IoMT-based glucose monitoring study with 283 participants (mean age 60 years; 57.4% male, 42.6% female; all of Indian ethnicity) [75].
- Diabetes progression prediction using data from the Pinggu cohort (622 participants) and the Beijing Prediabetes Reversion Program (1,936 participants) [78].
- ECG-based diabetes screening with 1,262 individuals from the Sindhi population in Nagpur, India (61% female, average age 48 years, 30% diabetes prevalence, 14% pre-diabetes prevalence) [86].
- The wid[77].

d) Recent Studies on Predictive Modeling and Wearables: Additional experimental studies include,

- PPG recordings for non-invasive Type II diabetes prediction (demographic details not provided) [81].
- Machine learning models applied to lab test data for diabetes and hyperthyroidism [82][83].
- Wearable sensors for prediabetes detection with 22 participants (10 prediabetic, 12 normoglycemic; 13 men, 9 women) [85].
- ML-based classification using PPG signals from 97 subjects (59 non-diabetic, 38 diabetic) [87]

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- CNN-based AI/ML models applied to pulse wave analysis using 2,000 pulse wave samples, equally split between healthy and diabetic individuals [89].

Overall, the studies exhibit considerable variation in sample sizes and demographic details, with some providing extensive breakdowns and others synthesizing data from multiple cohorts.

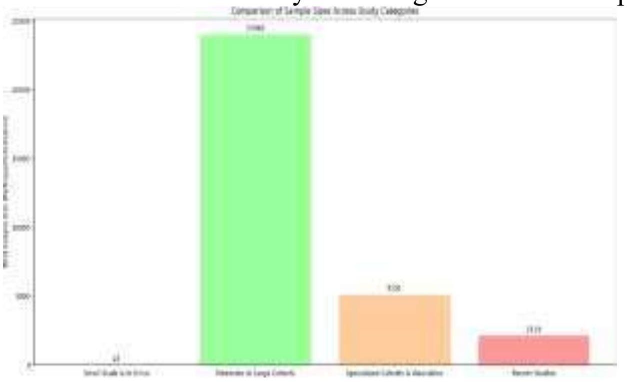

Fig. 3: Comparison of sample sizes and demographic characteristics across studies.

4) Key Research Questions : The studies address several central themes using AI/ML techniques. The primary research questions include:

1. **Glucose Prediction, Control, and Risk Models**

- **Algorithm Comparisons and Innovations:**

– Evaluating multitask learning versus sequential transfer learning for personalized blood glucose prediction [6].
– Assessing the performance of convolutional recurrent neural networks (CRNN) and ensemble deep learning models to improve predictive accuracy [9][11][16][17][36][39].
– Proposing novel methodologies such as the Average Weighted Objective Distance (AWOD) for type-2 diabetes prediction [37].

- **Reinforcement Learning and Alternative Approaches:**

– Exploring the use of reinforcement learning (RL) for blood glucose control with an emphasis on safety and interpretability [33].
– Investigating the integration of Traditional Chinese Medicine (TCM) tongue diagnosis features with ML for diabetes risk prediction [61].

- **Personalized Diabetes Management and Progression:**

– Developing predictive models for insulin dosing and personalized management based on patient-specific factors [25][42].
– Integrating heterogeneous data sources (clinical, wearable, synthetic) to support real-time decision-making and personalized care [27][29][34].
– Stratifying individuals with prediabetes to evaluate their risk of progression to diabetes and to inform intervention strategies [78].

2. **Non-Invasive and Wearable Monitoring Systems**

- **Optical and Sensor-Based Technologies:**

– Assessing the feasibility and accuracy of non-invasive glucose monitoring using PPG signals, near-infrared spectroscopy (NIRS), multiple optical wavelengths, and fiber lasers [8][20][21][22][24][26][48][60].

- **Innovative Device Platforms:**

– Developing wearable systems and smartphone-integrated devices for continuous monitoring, such as the GlucoBreath system [40] and IoMT-enabled biosensors [7][14][25][28][31][50][63].
– Evaluating non-invasive approaches that use alternative biosignals—for instance, sweat glucose prediction [57] and integrated bio-signals for thermal comfort modeling [64].

- **Device-Focused Studies:**

– Evaluating wristband PPG signals for non-invasive blood glucose estimation [69].
– Assessing AI model performance using non-invasive wearable device data [70].
– Developing an IoT-based CGM system to provide continuous, non- invasive glucose insights [80].

– Creating user-friendly nomograms for diabetes screening using non-lab and semi-lab data in a large Chinese cohort [74].
– Designing a demography-agnostic, real-time monitoring system leveraging AI and IoMT validated on an Indian cohort [75]

- **Emerging Predictive Techniques from Biosignals:**

– Using publicly available PPG recordings to non-invasively predict Type II diabetes and determining the significance of specific PPG-derived features [81]
– Investigating novel loss functions for predictive models based on lab test data to improve healthcare modeling robustness [82].
– Improving diabetes diagnosis through general machine learning approaches on lab data [83]
– Exploring wearable sensors for prediabetes detection via continuous monitoring and inertial sensor data [85]
– Utilizing ECG data in a large-scale observational study to predict diabetes and pre-diabetes, offering a potential scalable screening tool [86].
– Classifying diabetic versus non- diabetic patients using non-invasive PPG signals from a publicly available dataset [87].
– Reviewing the progress and challenges in non-invasive blood glucose monitoring techniques and the potential role of AI/ML models in replacing traditional methods [88].
– Applying CNNs to analyze pulse wave samples for distinguishing diabetic from non-diabetic individuals [89]'

3. **Data Integration and Predictive Analytics**

- **Large-Scale and EHR-Based Prediction:**

– Integrating synthetic datasets with clinical data to enhance model robustness [27][34].
– Utilizing electronic health records (EHRs) for predicting health outcomes—including the prediction of depression and anxiety in T2D patients—via deep learning models [39][68].

- **Handling Data Challenges:**

– Addressing issues such as class imbalance and missing values to improve diabetes classification accuracy (e.g., via the PE_DIM algorithm) [46].

4. **Web-Based and IoT-Enabled Platforms**

- **Interactive Monitoring Systems:**

– Developing web-based monitoring systems and data-driven platforms for real-time diabetes management [34].
– Integrating wearable IoT sensor data with ML techniques to enhance long- term risk prediction, particularly in elderly cohorts [45].

5. **Comprehensive Reviews and Future Directions**

- **Systematic Reviews and Meta-Analyses:**

– Evaluating the effectiveness of ML and deep learning techniques in diabetes detection and management [53].
– Reviewing the application of ML in autoimmune diseases, including diabetes, and summarizing future research gaps [54].
– Synthesizing state-of-the-art developments in non-invasive glucose monitoring—from optical methods to e-textiles—and discussing challenges in accuracy, reliability, and usability[58][59][65][66][67][88].

- **Wearable and Mobile Health Innovations:**

– Assessing the feasibility of using smartphones for hypoglycemia prediction in diabetic patients [55].
– Evaluating the integration of electromagnetic sensors with AI/ML models in wearable glucose monitoring systems [56].
– Reviewing wearable technology's role in managing Type 1 diabetes, as surveyed in literature reviews [71].
– Summarizing recent advancements in wearable health monitoring technologies and continuous glucose monitoring systems
[72][73][76]

- **Predictive Models for Broader Outcomes:**

– Extending ML model applications to predict non-glucose-related outcomes, such as depression and anxiety in T2DM patients [68]
– Using classic datasets, such as the Pima Indians Diabetes Dataset, to refine diabetes prediction models [77]

- **Hypoglycemia Prediction:**

– Identifying predictive indicators of hypoglycemia in Type 1 Diabetes using wearable sensor data and shapelet-based features [79]

These research questions collectively illustrate the evolving role of AI/ML in transforming diabetes care—from developing non-invasive monitoring systems and personalized prediction models to integrating heterogeneous data sources for comprehensive disease management, predicting disease progression, and extending predictive capabilities using both wearable and traditional biosignals.

B. Wearable Sensor Technologies

Wearable sensor technologies play a pivotal role in the continuous monitoring of diabetes, especially in combination with Continuous Glucose Monitors (CGMs). These devices enable real-time tracking of blood glucose levels, thereby enhancing diabetes management and intervention strategies. Below, we discuss the main wearable sensor technologies used for glucose monitoring—including CGMs, smartwatches, fitness trackers, and smartphone-based solutions—and their integration into diabetes care.

1) Continuous Glucose Monitors (CGMs): CGMs are essential for continuous, real-time blood glucose monitoring in diabetes management. These devices provide vital information that aids in optimizing treatment regimens and improving overall patient outcomes. Numerous studies have highlighted the use of CGMs for blood glucose tracking, including devices such as Medtronic Enlite, Dexcom, and FreeStyle Libre sensors.

Several studies have utilized CGMs as the primary wearable sensor for collecting glucose data. For example, studies have reported the use of Medtronic Enlite CGM sensors and the Medtronic 530G insulin pumps as common devices for glucose monitoring [1][4][13]. Other widely used devices include Dexcom and FreeStyle Libre [8][9]. These sensors are noted for their accuracy in tracking time-series blood glucose levels, which is critical for effective diabetes management [50]

Moreover, some studies have emphasized the use of minimally invasive CGM sensors, such as microneedle-based sensors and flexible electrode devices [73]. These advancements help reduce patient discomfort while enhancing sensor accuracy.

2) Smartwatches, Fitness Trackers, and Smartphone- Based Solutions : In addition to CGMs, wearable devices such as smartwatches and fitness trackers are increasingly integrated into diabetes management. These devices capture additional physiological parameters such as heart rate, step count, skin temperature, and electrocardiogram (ECG) data, which can complement glucose monitoring.

For instance, smartwatches and fitness trackers using photoplethysmography (PPG) and ECG sensors offer supplementary monitoring that supports diabetes care. A study using the Empatica E4 wristband measured reflective PPG signals for cardiovascular monitoring [85], while other commercially available devices like the Zephyr Bioharness 3 capture physiological data relevant to heart rate and breathing [79].

Moreover, smartphone-based systems are frequently employed to capture data from wearables—particularly PPG signals obtained from devices such as smartwatches [8]providing an integrated mobile solution for continuous monitoring and data analysis.

3) Biomarker Integration and IoT-Enabled Solutions: The integration of biomarker sensors with IoT-enabled platforms further enhances the potential of wearable sensor technologies. For example, some systems combine glucose sensors with IoT technology to provide continuous monitoring of glucose levels alongside biomarkers like salivary cortisol [64]. These IoT-enabled solutions allow for seamless data collection and real-time tracking, which is essential for timely interventions in diabetes management [80].

4) Summary of Studies Using Wearable Sensors: Table 2 summarizes the studies that have utilized wearable sensor technologies—including CGMs, smartwatches, fitness trackers, and smartphone-based solutions. The table provides an overview of the devices used in each study and highlights the emphasis on continuous glucose monitoring as a primary tool in diabetes care.

Study	Wearable Sensor(s) Used	Devices	Reference
Study 1	CGM, Fitness Tracker	Medtronic Enlite CGM, Activity Bands	[1]
Study 2	CGM	Medtronic Enlite CGM	[4]
Study 3	CGM	Dexcom, FreeStyle Libre	[9]
Study 4	CGM	Medtronic Enlite CGM	[28]
Study 5	CGM	Dexcom	[50]
Study 6	CGM	Medtronic Enlite CGM	[52]
Study 7	PPG, ECG Sensors	Empatica E4, Other Wearables	[85]
Study 8	ECG, Other Sensors	Zephyr Bioharness 3	[79]
Study 9	Smartphone-Based Systems	Various Smartwatches	[8]
Study 10	CGM, IoT	Dexcom, IoT-Enabled Sensors	[64]

TABLE 2: Summary of Studies Using Wearable Sensors for Diabetes Monitoring

5) *Noninvasive Optical, Electrochemical, and PPG- Based Biosensors:* Noninvasive biosensors, including optical, electrochemical, and photoplethysmography (PPG)- based technologies, are revolutionizing the field of glucose monitoring. These sensors offer key advantages over traditional methods, such as reduced discomfort for patients and continuous monitoring capabilities, making them suitable for wearable devices. The following subsections outline the key developments and applications of these biosensor technologies:

a)Photoplethysmography (PPG) and Near-Infrared (NIR) Techniques: PPG and NIR techniques are pivotal for noninvasive glucose monitoring. They measure physiological signals such as blood volume and oxygen saturation that correlate with glucose levels.

– **Photoplethysmography (PPG) Sensors:** PPG sensors measure blood volume changes through light absorption/reflection and are commonly integrated into wearable devices. Recent studies demonstrate that PPG can detect glucose fluctuations by analyzing blood volume changes [22].

– **Near-Infrared (NIR) Photoplethysmography (NIR-PPG):** NIR-PPG sensors capture a broader spectrum of light compared to standard PPG sensors. This enhanced sensitivity allows for more accurate glucose level readings. By using near- infrared light, these sensors reduce the interference caused by skin pigmentation and other factors, improving the signal-to-noise ratio [23].

– **Infrared Pulsed Sensing (IPS):** Infrared pulsed sensing (IPS) is another advanced PPG-based technique. IPS systems measure changes in blood flow that are directly related to glucose levels, providing an effective method for glucose monitoring [24].

6) Custom Optical Biosensors and Fiber Laser-Based Systems: Beyond standard PPG/NIR sensors, custom optical biosensors and fiber laser-based systems offer enhanced sensitivity and precision for noninvasive glucose monitoring.

a) ***Custom Optical Sensors:*** Custom-designed optical sensors, developed to specifically detect glucose concentrations, offer high sensitivity and precision. These sensors are often integrated into portable or wearable devices, making them ideal for continuous glucose monitoring [26].

b) ***Vis-NIR Optical Biosensors:*** Vis-NIR optical biosensors use both visible and near-infrared light to detect glucose levels. These sensors can capture glucose absorption spectra more effectively, providing more accurate readings in real-time [31].

c) ***Fiber Laser-Based Optical Devices:*** Fiber laser- based optical sensors represent a promising advancement in glucose monitoring. These devices utilize the scattering properties of glucose molecules to detect glucose concentrations, providing high-resolution measurements [60].

7) Biosensors for Alternative Biofluids: Noninvasive glucose monitoring is not limited to skin sensors. Alternative biofluids such as sweat, tears, and interstitial fluid are also being explored:

a) ***Glucose Measurement in Sweat and Tears:*** Recent studies have demonstrated the feasibility of measuring glucose levels in sweat and tears. These biofluids can be used as indicators for glucose concentrations, offering a non- invasive approach to glucose monitoring [72].

b) ***Integration with IoT Devices:*** Some systems integrate noninvasive glucose monitoring into Internet of Medical Things (IoMT) networks. These devices use sensors placed on the skin to measure glucose from alternative biofluids, providing continuous monitoring capabilities [75].

8) Additional Optical and Electrochemical Biosensors: In addition to PPG and optical biosensors, other techniques, such as dual-wavelength PPG sensors and hybrid optical- electrochemical systems, are under investigation to improve glucose monitoring accuracy.

a) Dual-Wavelength PPG Sensors: Dual-wavelength PPG sensors use both red and infrared light (typically at 660 nm and 905 nm) to improve the precision of glucose monitoring. These sensors enable more accurate readings by compensating for external factors like skin tone [81].

b) Electrochemical, Optical, and Microwave Sensors: Electrochemical, optical, and microwave sensors are being combined in innovative systems to enhance glucose monitoring. These multi-modal devices enable the simultaneous measurement of glucose levels, heart rate, and other health parameters [88].

c) Multi-Modal and Novel Sensing Platforms: The integration of multiple sensing modalities into a single platform is a promising direction in noninvasive glucose monitoring. These multi-modal systems combine glucose sensors with other physiological sensors to provide a more comprehensive understanding of a patient's health. *Integrated Multi-Modal Systems:* Multi-modal platforms integrate glucose sensors with additional sensors, such as ECG, accelerometers (ACC), and respiratory sensors. This integration allows for continuous glucose monitoring alongside other vital signs, offering a holistic view of patient health [2][10].

d) Combination of ECG and PPG Sensors: Some wearable devices combine ECG and PPG sensors for enhanced glucose monitoring. This combination enables more accurate assessments of glucose levels while also monitoring cardiovascular health, which is critical for patients with diabetes or prediabetes [49].

9) IoT-Enabled and Custom-Designed Wearables: The rise of the Internet of Things (IoT) has enabled the development of connected wearable devices for continuous glucose monitoring. These devices offer real-time data collection, enabling timely interventions.

a) IoT-Enabled Devices : IoT-enabled medical devices, such as the VOC-Analyser, integrate electrochemical sensors to monitor glucose levels and other health metrics. These systems transmit data to healthcare providers, enabling remote monitoring and better decision- making[40].

b) Custom-Designed Wearables: Custom-designed wearable devices, including garments with integrated electromagnetic (EM) sensors, provide a comfortable and unobtrusive method for continuous glucose monitoring. These wearables adapt to movement and physical activity, making them ideal for long-term monitoring [56]

10) Emerging Integration into Textiles

The integration of sensors into textiles has created opportunities for continuous glucose monitoring systems that are both comfortable and flexible.

a)Multi-Modal Textile Systems: Recent research has focused on embedding sensors in textiles to create multi-modal systems. These systems integrate optical, biochemical, biomechanical, and thermal sensors to continuously monitor glucose levels and other physiological parameters. E-textiles offer an innovative, flexible solution for long-term use [59][66].

11) Challenges and Insights in Implementation

While wearable sensors and noninvasive monitoring techniques have made significant progress, several challenges remain, including sensor accuracy, data quality, and integration with existing healthcare infrastructure.

a) Alternative Data Sources and Non-Wearable Focus: Some studies are exploring alternative data sources, such as clinical variables and laboratory tests, as opposed to wearable sensors, to develop more accurate predictive models for glucose levels [78].

b) Challenges in Data Quality and Integration: Ensuring high-quality data collection remains a challenge. Issues like sensor accuracy, inconsistent timestamps, and data gaps can undermine the performance of predictive models. Addressing these challenges is crucial for the effective use of noninvasive glucose monitoring [77][82].

12) Real-World Clinical Impact

The use of noninvasive glucose monitoring in clinical settings has led to significant improvements in patient outcomes, including better disease management, early detection, and personalized treatment strategies.

a) Clinical Benefits: Wearable noninvasive glucose monitoring systems have been shown to improve patient outcomes by enabling real-time monitoring of glucose levels, providing more precise insulin dosing, and preventing severe hyperglycemic or hypoglycemic events [78][83].

C. AI/ML Models in Diabetes Monitoring

The advent of wearable sensor technology, coupled with rapid advances in artificial intelligence (AI) and machine learning (ML), has led to transformative changes in diabetes monitoring and management. Researchers have developed a broad spectrum of AI/ML models that aim to predict blood glucose (BG) levels noninvasively, detect hypoglycemic events, support insulin dosing decisions, and assess both diabetes risk and disease progression. In many cases, these models integrate data from multiple sensor modalities— such as photoplethysmography (PPG), near-infrared (NIR) spectroscopy, electrocardiography (ECG), optical sensors, and even acceleration or breath analysis—to generate personalized, real-time predictions. This section provides an extensive review of the literature, integrating findings from citations [1][89], and is organized by the type of model used, the algorithms implemented, performance metrics, and prospects for personalization and multi-modal data integration.

1) Types of AI/ML Models : The AI/ML techniques applied to diabetes monitoring can be broadly categorized into supervised learning models, reinforcement learning methods, and system-level approaches focusing on the integration of IoT technologies with sensor data. Each category addresses specific challenges and applications in diabetes care.

a)Supervised Learning Models : Supervised learning is by far the most extensively employed approach in diabetes monitoring applications. These models are typically trained on labeled datasets where input features (e.g., sensor-derived physiological parameters) are mapped to target outcomes (such as BG levels or diabetes status). The following subcategories represent the diversity of supervised learning applications in the literature:

- **Multitask, Transfer, and Traditional Classifiers:** Studies[1][6] utilize multitask learning frameworks, which allow models to learn shared representations across multiple tasks or subjects. In these studies, deep learning models are compared with support vector regression (SVR) to leverage the shared information across different individuals. This approach is particularly valuable in scenarios where subject- specific data may be limited, thereby enabling personalized glucose prediction even with sparse training examples. Early in vestigations[2][5] applied conventional algorithms such as Support Vector Machines (SVM), Decision Trees (DT), and K-Nearest Neighbors (KNN) to predict BG levels or assess overall metabolic health. For instance[34], explores a combination of classifiers—including DT, SVM, Random Forest (RF), gradient boosting, Multi-Layer Perceptron (MLP), and Naive Bayes—to classify individuals into normal, pre-diabetic, or diabetic groups.
- **Deep Learning and Recurrent Architectures:** A large body of Work [4][7][9][12][13][14]17][28][30][66] focuses on recurrent neural network (RNN)- based models, especially Long Short-Term Memory (LSTM) networks and Gated Recurrent Units (GRU), to capture the temporal dynamics inherent in BG fluctuations. For example, study[9] presents a convolutional recurrent neural network (CRNN) that combines convolutional neural network (CNN) layers for robust feature extraction with LSTM layers for modeling temporal dependencies. Similarly,[14]employs a GRU-based model enhanced with evidential regression to provide early warnings

of hypoglycemia. Other studies[1][22][24] incorporate CNNs, hybrid architectures (such as the deep hybrid DCC-Net), and even Transformer-based models (e.g., GPFormer) to facilitate multi-horizon BG prediction from noninvasive signals like PPG.

- **Hybrid and Ensemble Methods:** Research such as[29][36] illustrates the power of ensemble deep learning (EDL) models, which combine multiple base learners (e.g., ANN, LSTM, CNN) via stacking or meta-modeling. By aggregating predictions from various models, ensemble methods typically achieve higher robustness and improved accuracy. Hybrid models, like that in[16][19], integrate deep feature extraction with traditional AI for classification or leverage transfer learning (e.g., TrAdaBoost with Extreme Learning Machines) to enhance BG prediction.
- **Screening, Risk, and Progression Prediction:** Studies[55][56] focus on hypoglycemia prediction and BG forecasting using algorithms such as J48 decision trees, Fuzzy Lattice Reasoning (FLR), and Gaussian Process Regression (GPR) with specialized kernel functions. In[74] multivariable binary logistic regression is used to construct nomograms for predicting undiagnosed diabetes from noninvasive data, thereby enhancing early detection and screening efficiency. In[78], the XGBoost algorithm is employed for predicting the 1-year diabetes progression risk in individuals with prediabetes. XGBoost was selected for its superior performance (accuracy and F1 score) compared to logistic regression, RF, SVM, and decision trees. This work underscores the potential for personalized treatment strategies and suggests that future research should explore multi-modal data integration.
- **Recent Developments and Additional Applications:** Recent studies further illustrate the potential of AI/ML for diabetes monitoring. In[69], SVR and Extreme Gradient Boost Regression (XGBR) are used for BG estimation based on features extracted from PPG signals and physiological parameters, with recommendations to explore additional data modalities. Study[70] employs both traditional (RF, SVR) and deep learning models (MLP, ANFIS) for glucose prediction from wearable device data, highlighting opportunities for multi-modal integration. Papers[71][72] discuss ML strategies that focus on near-future glucose prediction and real-time analytics, addressing imprecision in lab test data and timestamps. In [73] deep learning models including CNNs, RNNs, decision trees, SVMs, and LSTM networks are used for personalized treatment planning, with potential applications in artificial pancreas systems. Furthermore[77], employs a range of supervised models (logistic regression, SVM, RF, gradient boosting, K-nearest neighbors, decision trees) for predicting the onset of diabetes and classifying individuals by risk.
- **Additional Specialized Studies and Emerging Trends:**
- Recent

Research [81][82][83][85][86][87][88][89]

further refines supervised learning applications. For example[81], applies Random Forest and XGBoost to classify PPG signals into diabetic (Type II) or normal categories, with XGBoost showing superior performance. Study[82] employs LSTM networks and Random Forest classifiers for disease progression prediction, while[83] discusses various ML models (Naive Bayes, decision trees, RF, SVM, neural networks) for early diabetes diagnosis. In[85], SVMs with radial-basis function kernels classify individuals as normoglycemic or prediabetic using features extracted from both glucose and acceleration data. Study[86] uses XGBoost on ECG data to classify subjects into "no diabetes," "pre-diabetes," or "type 2 diabetes" categories, and[87] uses Logistic Regression and XGBoost for classifying diabetic versus non-diabetic patients based on PPG features. Future trends in noninvasive monitoring are discussed in[88],while[89] employs supervised learning with CNN architectures (including conventional CNN, VGG16, and ResNet18) to classify pulse wave images for diabetes prediction.

b) Reinforcement Learning Models: Although supervised learning is the most common approach, reinforcement learning is emerging as a promising methodology for adaptive control in diabetes management. In[33], a soft actor-critic (SAC) network—guided by proportional-integral-derivative (PID) control—is combined with random forest regression (RFR) and a dual attention network (DAN) to predict BG levels and determine insulin dosing. This strategy is designed to enhance safety, interpretability, and personalization in clinical interventions. Additionally, reviews such as[54] include reinforcement learning as part of integrated decision-support systems that provide both insulin recommendations and hypoglycemia predictions.

2) AI/ML in IoT-Based and Noninvasive Systems : Some studies focus on system-level integration rather than purely on algorithmic innovations. For example[80] discusses the development of an IoT-based continuous glucose monitoring (CGM) system that emphasizes real-time data transmission and robust sensor networks. Although specific AI/ML models are not detailed in this work, the emphasis on system integration underscores the importance of reliable sensor data for advanced diabetes management.

3) Additional Perspectives and Reviews : Recent reviews [53][54][57][58][59][60][62][63][64][66][67][68].

provide comprehensive overviews of various AI/ML models—from traditional machine learning techniques to deep and reinforcement learning—and consistently emphasize the need for personalized approaches via multi-modal data integration. These reviews highlight the challenges posed by data imprecision and heterogeneity in real-world settings and call for a convergence between algorithmic innovations and their practical applications in wearable sensor technologies for diabetes care.

4) Recent Specialized Studies : Additional recent studies have further refined these approaches:

- In[81], Random Forest and XGBoost are applied to classify PPG signals into diabetic (Type II) or normal categories, with XGBoost showing superior performance. The study recommends integrating additional data sources to personalize the model.
- In[82], LSTM networks and Random Forest classifiers are used for disease progression prediction, addressing issues related to imprecision in lab test data and timestamps, and suggesting personalized and multi-modal integration for future work.
- In[83], a range of ML models (Naive Bayes, decision trees, RF, SVM, neural networks) are evaluated for early diabetes diagnosis.
- In[85], SVMs with RBF kernels classify individuals as normoglycemic or prediabetic using features derived from both glucose and acceleration data.
- Study[86], applies XGBoost to ECG data for classifying individuals into "no diabetes," "pre- diabetes," or "type 2 diabetes" categories, with recommendations to incorporate demographic and comorbidity data.
- In[87] Logistic Regression and XGBoost are used for classifying diabetic versus non-diabetic patients based on PPG signal features, emphasizing the need for personalized models.
- Future trends in noninvasive glucose monitoring are discussed in [88] focusing on the potential use of AI/ML for glucose prediction and insulin recommendations, along with a focus on personalized medicine.
- Finally, in[89] supervised learning using CNNs (including conventional CNN, VGG16, and ResNet18) is applied to classify pulse wave images for diabetes prediction, with an emphasis on personalized medicine and multi-modal data integration.

5) Algorithms Used: The algorithms employed across these studies span a wide range—from state-of-the-art deep learning architectures to classical machine learning methods. The details are as follows:

a) Deep Learning Architectures:

- **Recurrent and Convolutional Models:** LSTM, GRU, cascaded BiLSTM, and attention-based RNNs are widely used to model the temporal evolution of BG levels [4, 7, 9, 12, 13, 14, 17, 28, 30, 66].

CNNs, including CRNNs and Transformer-based models such as GPFormer [11], are employed for robust feature extraction from complex sensor signals.

- **Hybrid and Ensemble Approaches:** Novel architectures such as the deep hybrid DCC-Net [24] and GlucoNet [75] combine spatial and temporal feature extraction. Ensemble methods, including stacking approaches [29]36][44][46], [48] integrate multiple base learners (e.g., ANN, LSTM, CNN) to boost overall performance.
- **Recent Developments:** Studies [81][86][87] highlight the use of XGBoost and Random Forest algorithms for classifying physiological signals (PPG, ECG), while [82][85] integrate LSTM networks with SVM (using an RBF kernel) to improve prediction and classification tasks.

*b) Traditional Machine Learning Methods***:** Widely used algorithms include SVM, decision trees, KNN, Random Forest, logistic regression, and Gaussian Process Regression [2][5][8][18][23][53][63].

Additional techniques include Extreme Gradient Boost Regression [ref69], Adaptive Neuro-Fuzzy Inference System (ANFIS) [70], and multivariable logistic regression [74]. In [78] and [87], XGBoost is emphasized for its superior accuracy and F1 score.

- Reinforcement Learning: The soft actor-critic (SAC) network in [33] is an example of combining reinforcement learning with classical control (PID) and auxiliary regressors (RFR, DAN) for dynamic insulin dosing.
- Optimization and Time-Series Forecasting: Time- series models such as ARIMA and SARIMAX, along with optimization algorithms (e.g., Genetic Programming, Particle Swarm Optimization), are employed to support BG forecasting and optimize insulin recommendations [76].
- Additional Implementations: Several reviews [67] and studies [71, 72] discuss the integration of big data approaches and general ML strategies to further improve the accuracy and personalization of predictive models.

6) Performance Metrics and Personalized Approaches: Model performance is rigorously evaluated using a variety of quantitative metrics, and many studies emphasize strategies for personalization and multi-modal data integration.

a) Classification Metrics: For classification tasks (e.g., hypoglycemia detection, diabetes diagnosis, and risk classification), common metrics include accuracy, precision, recall, F1-score, and the area under the receiver operating characteristic curve (AUC-ROC) [8][15][41][46][52][63][78][83][87].

b) Regression Metrics: For continuous BG prediction, performance is typically measured using Mean Square Error (MSE) (e.g., an MSE of 5.79 reported in [25]), correlation coefficients (e.g., 0.90 in [48]), and prediction horizons (e.g., a 30-minute forecast in [28].

c) Personalized Approaches and Multi-Modal Integration: Many studies [1][6][56][59][61], [63][64][66][69][70][71][72][73][77][79] emphasize the importance of developing personalized models that account for individual variability (e.g., physiological, lifestyle, and environmental factors) and integrating multiple sensor modalities (e.g., PPG, ECG, acceleration, optical signals) to enhance prediction accuracy and clinical relevance. Specific recommendations include:

- Exploring the use of PPG-only feature sets in combination with additional data streams [69, 87].
- Utilizing shapelet-based feature extraction to capture subtle patterns in sensor data [79].
- Incorporating demographic and comorbidity information to tailor models to diverse patient populations [86].

7) Summary: In summary, the literature on AI/ML models for diabetes monitoring is extensive and multifaceted. Supervised learning techniques—spanning deep learning architectures (RNNs, CNNs, Transformers), traditional machine learning methods (SVM, RF, logistic regression), and ensemble/hybrid models—dominate applications for noninvasive BG prediction, hypoglycemia detection, and diabetes risk screening/progression estimation. Reinforcement learning approaches, such as the soft actor- critic network described in [33], offer promising avenues for adaptive insulin dosing and real-time decision support. Recent studies [81]–[89] further illustrate the growing use of advanced algorithms (e.g., XGBoost, LSTM, CNNs) for classifying physiological signals and predicting disease progression, while consistently underscoring the importance of personalized approaches and multi-modal data integration. Although some works (e.g., 80]) focus primarily on IoT-based CGM systems without explicit AI/ML analytics, the overall trend is one of convergence: advanced algorithmic strategies are increasingly integrated with wearable sensor technology to deliver accurate, robust, and individualized diabetes management solutions. These efforts promise not only to enhance prediction accuracy and clinical decision- making but also to pave the way for tailored, patient-centric approaches that address the inherent heterogeneity in diabetes.

8) Performance Metrics for AI/ML Models: In this section, we provide a comprehensive review of performance metrics reported across studies evaluating AI/ML models for glucose prediction and related health monitoring tasks. The discussion is organized around key metrics — accuracy (and associated error metrics), sensitivity and specificity, AUC-ROC (and related diagnostic measures), and additional performance indicators — to offer a detailed view of model performance. The literature reveals both the strengths of various models and notable gaps in reporting, particularly when comparing sensor types and presenting metrics such as AUC-ROC, precision, and recall.

a) Accuracy and Error Metrics: Accuracy is one of the most frequently reported performance measures and is often accompanied by error metrics such as RMSE (root mean squared error), MARD (mean absolute relative difference), and MAE (mean absolute error). For example, several studies report RMSE values for both simulated scenarios (e.g., RMSE = 9.38 ± 0.71 mg/dL for a 30-minute horizon) and real patient datasets (e.g., RMSE = 21.07 ± 2.35 mg/dL) [ref1, ref9]. Other works indicate an RMSE of 1.67 mmol/L with a MARD of 17.88% [22] and a system mARD of 6.9% [23]. Reported accuracy values vary widely: some systems achieve 81.49% accuracy [8], while clinical systems have reported accuracies as high as 99.01% [56]. For instance, the DCC-Net model achieved an accuracy of 0.92 on the IPS-PPG dataset [24], and one glucose measurement system reported an average accuracy of 98.7% [25]. Hybrid approaches such as stack-ANN have achieved accuracies of 99.51%, 98.81%, and 98.45% on different datasets [29], and the AWOD method has reported accuracies of 93.22% and 98.95% on separate datasets [37]. Additionally, novel loss functions (e.g., IR loss) have been shown to improve prediction accuracy compared to traditional cross-entropy loss [ref82], with one study reporting 96% accuracy for its best-performing feature subset [81].

b) Sensitivity and Specificity: Sensitivity (the true positive rate) and specificity (the true negative rate) are critical for detecting conditions such as hypoglycemia and hyperglycemia. While some studies report detailed values — for example, one study noted a sensitivity of 0.92 and a specificity of 0.85 for a specific feature set [85] — many works focus primarily on accuracy and error metrics, with sensitivity and specificity reported less consistently [2][5][12][14][16][17][44][51][52][46][67]. In certain cases, multisensor systems have been shown to enhance performance, with one system demonstrating a lower MARD (2.8%) compared to standalone sensors [56].

c) AUC-ROC and Related Diagnostic Metrics: The area under the ROC curve (AUC-ROC) is a key measure of a model's diagnostic ability. Some studies report high AUC- ROC values — for example, one investigation recorded an AUC-ROC of 0.987 alongside an accuracy of 98.4% and an F1-score of 0.962 [40]. Other works report AUC-ROC values ranging from 0.69 to 0.83, with improvements noted when additional demographic data are included [21]. Detailed metrics from a stacking model showed an accuracy of 71%, an AUROC of 0.87, and an AUPRC (area under the precision-recall curve) of 0.77 on one dataset [61]. In another study on diabetes progression, an ML-PR model achieved an AUC of 0.80 (i.e., 80%), although other metrics were not explicitly mentioned [78]. Additional reports include ANN models with corresponding AUROC and AUPRC values [ref64, ref68]. Nevertheless, several studies either omit AUC-ROC data or discuss it only conceptually [33][51][52][53][54].

d) Additional Performance Metrics: Beyond the primary metrics, many studies report supplementary indicators that further characterize overall model performance:

- **Correlation and Regression Metrics:** High linear correlations (e.g., R2 ≈ 0.913) have been reported between sensor responses and actual blood glucose levels [ref30], with some studies also reporting correlation coefficients (e.g., 0.86) and standard prediction errors (e.g., 6.16 mg/dL) [31][48].
- **Traditional Classification Metrics:** Metrics such as precision, recall, F1-score, and MCC are commonly provided. For example, a CNN model evaluated for heart rate data analysis demonstrated high accuracy, precision, recall, and F1-score, while a Random Forest Classifier ~~showed~~ Showed notable performance with breathing rate data [ref79].
- **Feature Set Comparisons:** One study compared different feature sets and reported that a particular set (denoted as QhQcQ$_h$ Q$_($c$_)$QhQc) achieved an accuracy of 86%, a sensitivity of 92%, a specificity of 85%, and an AUC-ROC of 90% [85].
- **Model Comparisons:** Comparative analyses between Logistic Regression (LR) and XGBoost have shown differences in performance. For instance, one study reported that LR achieved an accuracy of 70.0%, a sensitivity of 66.4%, a specificity of 75.1%, a precision of 61.1%, an AUC-ROC of 79.2%, and an F1-score of 58.8% [87], whereas XGBoost achieved an accuracy of 64.5%, a sensitivity (recall) of 56.3%, a specificity of 70.5%, and a precision of 54.0% [87]. Furthermore, XGBoost has been noted to outperform other models in terms of accuracy and F1-score [81][86].
- **Deep Learning Architectures:** Studies focusing on image or signal data for diabetes diagnosis have compared various architectures. For example, one CNN achieved a testing accuracy of 80.6% [89]; VGG16 achieved a testing accuracy of 86.57% [89]; and ResNet18 achieved a testing accuracy of 92.00%, a precision of 93.20%, a recall of 91.43%, and an F1-score of 92.31% [89].
- **Non-Invasive Measurement Correlations:** One study reported a high correlation (0.9) between non-invasive measurements and actual blood glucose levels, indicating high measurement accuracy [88].

e) Summary: The literature on AI/ML models for glucose monitoring and related health tasks demonstrates that while metrics such as accuracy, RMSE, and MARD are widely reported, there is considerable variability—and sometimes a lack of detail—in the reporting of sensitivity, specificity, and AUC-ROC. Comparative studies suggest that advanced approaches, including hybrid ensemble methods and deep learning architectures (e.g., ResNet18), tend to deliver superior performance in terms of precision, recall, and F1-score. Nevertheless, standardized and comprehensive reporting practices are needed across studies, particularly regarding comparisons across different sensor types.

- **Detailed Performance Metrics Table**: Figure 4 summarizes detailed performance metrics of various AI/ML models and feature sets as reported in the literature.
- **Performance Metrics for AI/ML Models** Model performance is rigorously evaluated using a variety of quantitative metrics. The literature discusses accuracy (and error metrics like RMSE, MARD, MAE), sensitivity and specificity, AUC-ROC (and related diagnostic measures), and additional performance indicators. Comparative studies show that while some systems achieve high accuracies (up to 99.01% in certain cases), there is variability in sensitivity, specificity, and AUC-ROC reporting. In addition, supplementary metrics—such as correlation coefficients, precision, recall, F1-score, and comparisons between models (e.g., Logistic Regression vs. XGBoost, various CNN architectures)—provide deeper insights into model performance. Personalized approaches and multi-modal data integration are emphasized to tailor models to individual variability and enhance prediction accuracy.

D. Integration of AI/ML with Wearable Devices

1) Real-Time AI Integration: Researchers have developed a wide spectrum of AI/ML approaches embedded in wearable devices to support real-time diabetes management. These systems continuously capture physiological data and leverage advanced computational models to deliver immediate predictions and personalized treatment recommendations. Key integration strategies include:

• **Diverse Sensor Modalities and Data Streams:** AI models have been integrated with continuous glucose monitoring (CGM) systems

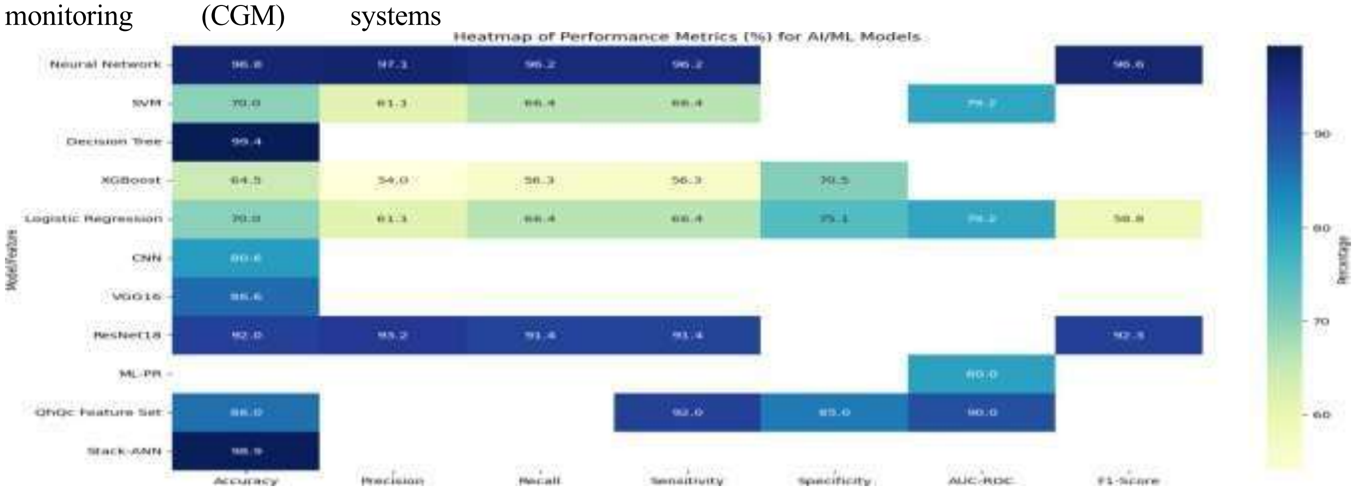

Fig 4 : Heatmap of Performace Metrics

[11][17][38][50][51]photoplethysmography (PPG) sensors [8,20,22,63,69,75,87]optical sensors [41,60]environmental and EM sensors [56] , and even nontraditional inputs such as sweat, tongue images, or tear analysis [57,61,62]. For example, one study integrates AI with a wearable PPG sensor to provide real-time blood glucose level predictions, offering a low-cost and convenient solution for continuous monitoring [69]. Other research leverages continuous data streams from wearable devices for blood glucose predictions [70].

• **Advanced Computational Techniques and Adaptive Systems:**
Techniques such as hierarchical feature fusion and cross-layer interactions refine predictions from sensor signals [22]. Reinforcement learning has been applied to simulated glucose dynamics, enabling systems to adapt to physiological changes without extensive prior data [33]. Several systems integrate AI to enhance decision-making in type 1 diabetes (T1D) management [71] and to enable automated insulin adjustments and personalized treatment strategies [73]. In addition, some platforms combine data from CGM devices with inputs such as insulin doses and meal intake to predict blood glucose levels (BGL) in ~~real~~ real-time [76].

• **Feature Extraction and Non-Invasive Diagnostics:**
Some studies focus on minimizing computational complexity by emphasizing feature extraction and applying traditional machine learning techniques rather than deep learning. For instance, one study integrates AI with PPG sensors for real-time, non-invasive diabetes predictions using shapelet-based analysis [81]. Other work employs CGMs and smartwatches to collect data for real-time prediabetes predictions, facilitating early lifestyle changes by providing timely alerts [85]. Similarly, the integration of ECG data for real-time diabetes screening underscores the suitability of non-invasive signals for wearable applications [86]. Moreover, research demonstrating the integration of CNNs with pulse wave data emphasizes the potential for non-invasive diabetes screening and personalized healthcare solutions [89]. Additional studies highlight the potential for AI-powered wearables to enhance real-time glucose monitoring without invasive procedures [87][88].

2) *Embedded and Edge Processing:* AI models are deployed on diverse platforms—from system-on-chip (SoC) devices and Raspberry Pi units [14][24] to smartphone- based applications and cloud-connected wearable systems [48][55]. Some approaches allow for flexible processing on edge devices or via cloud computing depending on network conditions, thereby enabling real-time predictions and decision support [75].

3) *Integration Beyond Traditional Wearables:* Beyond conventional sensor integrations, certain studies extend AI applications to IoT-enabled systems [80] and smartphone image processing for tear-based glucose monitoring [62]. Although some systems focus on non- invasive risk prediction without detailing AI integration [80], their potential to complement wearable approaches further expands the scope of diabetes management.

4) *Additional Feature Extraction for Diagnostics:* Other studies emphasize reducing computational complexity through

robust feature extraction. For example, AI integration with PPG sensors for non-invasive diabetes predictions focuses on feature extraction rather than deep learning [81]. Similarly, systems using CGMs and smartwatches have been proposed for real-time prediabetes predictions, while ECG-based screening methods have been explored as cost-effective tools for diabetes detection
[85][86]. Furthermore, CNNs applied to pulse wave data have shown promise for early, non-invasive diabetes screening [89].

5) Challenges in Integration: Despite these promising approaches, several technical and practical challenges remain:

- **Data Quality and Signal Integrity:** Many systems encounter issues related to signal noise and motion artifacts. PPG sensors, for example, are vulnerable to motion-induced artifacts that require advanced filtering and feature extraction techniques [22][69]. Studies using shapelet-based analysis for hypoglycemia prediction must address model bias and ensure high- quality data [79]. Occasional errors in CGM sensor measurements and the need for larger, more diverse datasets further complicate data integrity [85][87].
- **Computational Power and Processing Efficiency:** Real-time predictions demand significant computational resources, often exceeding the capacities of portable wearable devices. Optimized processing—ranging from energy-efficient architectures to improved ASIC designs—is necessary to overcome CPU and memory limitations [70][71][56][75][76][86]. Research employing CNNs for pulse wave data also highlights the challenges of handling large datasets and complex models [89].
- **Energy Consumption and Battery Life:** Continuous monitoring and on-device processing drain battery resources rapidly, limiting long-term operation
[72][73][76][88].
- **Calibration, Adaptability, and Model Robustness:** Systems must address calibration errors (e.g., due to glucometer reading variations) and ensure robustness against external interference and data variability
[75]. Adaptive systems, such as those using reinforcement learning, require careful tuning to ensure safety, interpretability, and minimal bias [33]. Limited participant numbers and sample biases can also impact model generalizability [70][79][87].
- **Additional Constraints:** Specific sensor modalities bring unique challenges—for instance, ensuring sensitivity and selectivity in sweat glucose detection
[57] or accounting for occasional CGM measurement errors [85]. In some IoT-based systems, challenges related to computational power and
battery life ~~are~~ is less detailed, indicating the need for further research [80].

6) Clinical Impact: The clinical promise of AI-powered wearable systems in diabetes management is substantial:

- **Enhanced Monitoring and Timely Interventions:**
Real-time predictions enable proactive blood glucose management, reducing the need for invasive sampling [70][72][73][75]and potentially improving glycemic control while minimizing hypoglycemic events [54][63][73][76]. Systems employing shapelet-based analysis for hypoglycemia prediction [79] and CNN-based screening methods [89] further emphasize early detection and personalized interventions.
- **Personalized Treatment and Automated Decision Support:** By integrating predictive models with personalized inputs (e.g., meal intake and insulin dosages), these systems can provide tailored treatment recommendations that reduce the cognitive burden on T1D patients and enhance overall disease management [71][73]. Automated insulin adjustments based on continuous monitoring help mimic pancreatic functions, leading to improved glycemic regulation.
- **Improved Patient Compliance and Quality of Life:** Non-invasive, low-cost solutions based on wearable PPG sensors [81][87] and ECG data
[86] have the potential to improve patient compliance by reducing discomfort and the frequency of invasive procedures, thereby enhancing long-term management and quality of life.
- **Broader Public Health Benefits:** Approaches such as integrating CGMs with smartwatches for prediabetes prediction
[85] may encourage early lifestyle changes through timely alerts. Additionally, if validated externally, ECG-based screening tools like the DiaBeats algorithm could serve as cost-effective options in low-resource settings [86]. Continuous real-time data sharing via IoMT platforms [66][67] further facilitates remote monitoring and timely clinical interventions, potentially reducing healthcare burdens.

Overall, the integration of AI/ML with wearable devices is transforming diabetes management by providing continuous, real-time, and non-invasive monitoring solutions. Although challenges remain regarding data quality, computational power, energy consumption, and sensor-specific constraints, ongoing advances in sensor technology, hardware

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optimization, and algorithm design continue to enhance system reliability and clinical impact. These integrated systems promise to reduce invasive monitoring, personalize treatment, and ultimately improve patient outcomes across diverse diabetic populations. Below it shows the Table 3 ~~as~~ Summarizing Key Integration Features and Figure 5 the Heatmap of Challenges vs. Clinical Impact Factors.
Below is the table in simple text format with the original content and citations intact:

Aspect	**Key Features**	**Example References**
Real-Time AI Integration	Continuous data capture; immediate predictions; personalized treatment	[11][17][38][50][51][70]
Embedded & Edge Processing	Deployment on SoC, Raspberry Pi, smartphones; flexible processing	[14][24][48][55][57]
Integration Beyond Traditional Wearables	IoT-enabled systems; smartphone image processing for tear-based monitoring	[80][62]
Additional Feature Extraction	Shapelet-based analysis; traditional ML for non-invasive predictions	[81][85][86][89]
Challenges in Integration	Data quality issues, computational power, energy consumption, calibration	[22][69][70][71][56][75]76][86][80]
Clinical Impact	Enhanced monitoring; personalized treatment; improved patient compliance	[70][72][73][75][54][63][73][76][71][73][81][87][86][66][67]

Table 3 : Summarizing Key Integration Features

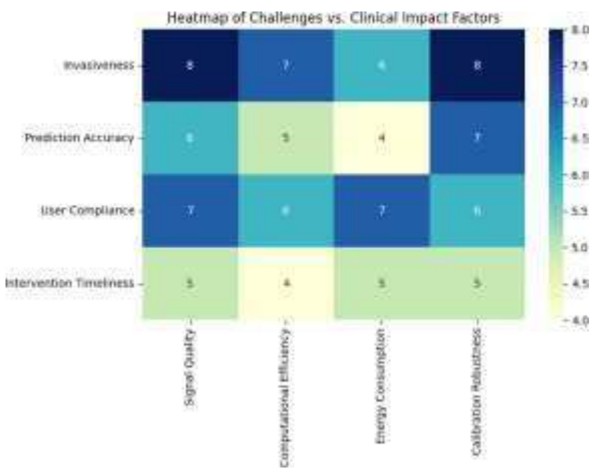

Fig 4: Heatmap of Challenges vs. Clinical Impact Factors.

E. Limitations and Biases

A review of the literature reveals a broad spectrum of limitations and biases that can affect the performance, accuracy, and generalizability of AI/ML models utilizing sensor data in contexts such as diabetes detection, prevention, and broader clinical applications. These challenges span issues related to data volume and quality, sensor accuracy and signal processing, algorithmic assumptions, and demographic representation.

1) ***Data and Model Limitations****:* Numerous studies report that limited individual data for training can lead to overfitting and insufficient personalized input [1][4][6]. Challenges include difficulties in classifying high-dimensional data [7] and issues with model reliability, user-friendliness, and generalization [15]. Specific approaches—such as the EDL model— face risks of overfitting and demand improved generalization capabilities [36]. In some cases, the reliance on a single patient or a homogeneous dataset raises concerns about the model's applicability to broader populations [55][53]. Additionally, the complexity of blood glucose dynamics and the need for accurate carbohydrate intake estimation are critical challenges for models aimed at diabetes prediction [54]. Furthermore, studies have highlighted the need for larger, multicentre validations to enhance model interpretability and robustness [78]. Other works note high false-positive rates and limitations arising from small sample sizes, which hinder reliable model evaluation [79]. Finally, some studies acknowledge that reliance on a single type of sensor or dataset could be a potential limitation.

2) ***Data Quality, Missing Data, and Preprocessing****:* Noise, missing values, and unexpected fluctuations are recurrent issues in sensor datasets [9]. Robust preprocessing and effective feature selection are necessary to mitigate these problems [45][46]. Several papers highlight imprecision in laboratory test data and stress the need for robust models capable of handling such variability [82]. In addition, issues with data quality and the complexity of clinical data can adversely affect model performance [83]. Occasional errors in continuous glucose monitoring (CGM) sensor measurements have been reported, and incomplete electronic health record (EHR) data further challenge model accuracy [68][85]. These data quality issues underscore the need for larger, more diverse datasets to enhance model generalizability [89].

3) ***Algorithmic Constraints and Model Assumptions****:* Certain advanced methods (e.g., reinforcement learning) require many training episodes and can introduce biases through assumptions inherent in structured models and simplified physiological dynamics [33]. Other approaches, such as the AWOD method, demand continuous adjustments due to the complexity of underlying health conditions [37]. These constraints complicate model design and evaluation, particularly when data are limited or imprecise [54].

4) ***Device and Environmental Constraints*** Controlled experimental environments often do not replicate real-world conditions, limiting the external validity of findings [22][40][56]. Wearable device constraints—such as the need for energy-efficient designs— add further challenges [28]. Moreover, issues such as data privacy, difficulties in data labeling within healthcare sensor systems (HCPS), and the lack of external validation in high-risk populations [86] complicate the translation of these models into clinical practice.

5) Sensor Limitations and Signal Processing :

- **Accuracy, Sensitivity, and Calibration**: Sensor data accuracy is a recurring concern. Multiple~~studies~~ Studies emphasize the need for enhanced sensor sensitivity and regular calibration to maintain prediction quality [8][25][32]. Noninvasive sensor methods, while promising, often struggle with maintaining sensitivity and selectivity—particularly in complex matrices like sweat [10][57]. Other research highlights challenges such as measurement imprecision, noise removal, and the overall complexity of data generated by wearables [71]. One study noted that the effects of motion artifacts on system performance were not investigated, a gap that may be critical in dynamic, real-world settings [69]. Maintaining sensor accuracy over time, including addressing deviations in glucometer readings and errors in CGM data, remains a persistent challenge [72][73][75][76]. Additionally, current noninvasive technologies are susceptible to interference and require further validation [88].
- **Signal Acquisition and Processing Challenges**: The extraction of meaningful information from sensor signals is often hampered by noise artifacts, motion interference, and the impact of fatty tissues [18][31]. Misalignment issues—such as synchronizing footprint images with sensor data— further complicate data processing [42]. Although multi-sensor integration offers a partial solution, additional real-world validation is necessary to overcome these limitations

[20][40][41]. Moreover, short durations of photoplethysmography (PPG) signals have been identified as a limitation, potentially affecting the robustness of models [87].

- **Specialized Conditions and Use-Cases:** Some studies focus on specific conditions, such as pregnancy, where model validation across different trimesters is essential [50]. In these contexts, sensor limitations may be exacerbated by physiological variations, underscoring the need for further in vivo research to complement in vitro findings [41]. Challenges in noninvasive methods have yet to be fully overcome to meet clinical standards [60].

6) Biases in Data Collection and Model Evaluation

- **Sample Representativeness and Demographic Constraints:** While many studies do not explicitly discuss biases, those that do point to issues related to non-representative samples and limited demographic diversity. For instance, low ratios of diabetic participants, uni-regional populations, or high-risk groups may limit the generalizability of results [22]. Some studies report that small sample sizes and the use of a single cohort can introduce population-specific biases [55][78]. Additionally, a small and potentially biased dataset—with occasional CGM measurement errors—can further skew model outcomes [85]. Studies focusing on high-risk populations or specific ethnic groups (e.g., a study limited to Indian ethnicity) may not generalize to broader populations, and high diabetes prevalence along with comorbidities can unduly influence model performance [70][74][75][86]. Biases may also arise from mixing PPG signals from the same patient during training and testing; however, some studies mitigate this risk by ensuring proper patient separation during cross-validation [87].
- **Experimental Environment and Data Distribution**: Biases can emerge from controlled experimental conditions that fail to capture real-world variability [22][40][56]. In vitro experiments might not fully represent in vivo complexities, leading to potential misrepresentations during model deployment [41]. Although some studies employ techniques such as oversampling or undersampling to address dataset~~-~~ imbalances [39], explicit discussions of data collection biases are generally limited. Efforts to minimize confounding variables—such as selecting healthy individuals free from other diseases—are noted, but bias due to limited sample diversity remains a concern [89].
- **Algorithmic and Data Balancing Biases:** Some research notes that inherent assumptions in AI/ML models, such as simplified representations of physiological dynamics, can result in biased outcomes [33]. While specific biases are often not detailed, reliance on a single type of sensor, limited datasets, and variability in device manufacturers can introduce additional challenges. A few studies imply that comprehensive validation is necessary to ensure model reliability, although explicit bias discussions are minimal [88].

7) **Summary***:* In summary, the literature underscores that pervasive challenges—ranging from limited data volume, sensor accuracy issues, and complex signal processing to constrained experimental conditions—impede the development of universally robust AI/ML models in healthcare. Concurrently, biases arising from non- representative samples, controlled environments, and inherent algorithmic assumptions further complicate model generalizability. Addressing these limitations and biases through improved sensor technologies, more diverse and robust datasets, advanced preprocessing techniques, and rigorous, multicentre study designs is essential for enhancing the clinical utility of AI/ML-driven health monitoring systems.

F. Future Research Directions

Advanced wearable health monitoring systems for diabetes have demonstrated significant promise through the integration of sensor technology and AI/ML models. However, to fully realize their potential in clinical practice and personalized care, further research is needed in several key areas. This section outlines the major directions for future work, providing a deeper insight into the technical and clinical challenges that must be addressed.

1) Enhancements in AI/ML Model Capabilities

a) Model Interpretability, Robustness, and Optimization: Current AI/ML models often operate as "black boxes," limiting clinical trust and hindering their integration into routine care. Future research should prioritize methods that improve interpretability—such as attention mechanisms, layer-wise relevance propagation, or rule extraction techniques—to ~~clearly~~ delineate how predictions are made [12][16]. Additionally, enhancing robustness against data variability (due to sensor noise or patient heterogeneity) through ensemble methods, adversarial training, and robust optimization frameworks is essential to ensure consistent performance across diverse populations.

b) Multi-Modal Data Integration and Fusion: Incorporating heterogeneous data streams—such as continuous glucose measurements, cardiovascular metrics, physical activity, dietary inputs, and stress indicators—can dramatically improve the predictive power of diabetes monitoring systems [2][10]. Advanced data fusion techniques, including multi-view learning and deep feature synthesis, should be explored to extract synergistic features from disparate data sources. Moreover, integrating contextual information (e.g., environmental conditions and behavioral patterns) could lead to more nuanced and accurate predictions of glycemic events.

c) Big Data Analytics and Adaptive Learning Frameworks: The performance of AI/ML systems is largely contingent on the quality and volume of available data. Future work must focus on expanding datasets and refining strategies for quantitative blood glucose measurement to capture fine-grained physiological variations [24]. Adaptive learning frameworks—such as online learning, transfer learning, and federated learning—offer promising avenues for continuously updating models in response to new data. This adaptability is critical for maintaining model accuracy over time as individual patient profiles evolve [13].

d) Integration with Cloud and Edge Computing: To support real-time analytics and decision-making, future research should explore hybrid computing architectures that combine cloud-based resources with edge computing. Such integration can minimize latency, facilitate distributed processing, and enable secure, scalable monitoring solutions, especially in resource-constrained settings. This approach also has the potential to support real-time model updates while ensuring data privacy through localized processing.

2) Advancements in Wearable Sensor Technologies

a) Development of Next-Generation Noninvasive Sensors: Recent research points to a shift toward noninvasive methods for continuous glucose monitoring, which can improve patient comfort and adherence [44]. Innovations in sensor materials, microfluidic designs, and optical sensing techniques are crucial for developing reliable noninvasive devices. These next-generation sensors should aim not only to enhance measurement accuracy but also to reduce energy consumption and improve long-term stability in real-world conditions.

b) Enhanced Biosensor Integration for Comprehensive Health Profiling: Beyond glucose monitoring, incorporating biosensors that detect additional biomarkers (e.g., lactate, cortisol, inflammatory markers) offers the potential for a holistic view of a patient's metabolic and physiological state [44]. Future systems should focus on creating interoperable sensor networks that can seamlessly combine multi-parameter data. This integration would facilitate early detection of non-communicable diseases (NCDs) and enable timely interventions, thereby extending the utility of wearable devices beyond diabetes management.

c) Sensor Network Scalability, Interoperability, and Security: As wearable sensor networks become more complex, ensuring seamless data transmission and device interoperability is essential. Research should address the challenges of network scalability by standardizing sensor calibration protocols and performance metrics. Moreover, with the increasing volume of sensitive health data, robust cybersecurity measures—including blockchain-based data integrity checks and advanced encryption methods—must be integrated into sensor networks to safeguard patient information.

3) Personalization and Predictive Accuracy in Diabetes Management

a) Patient-Specific Thresholds and Adaptive Protocols: Personalized diabetes management requires moving away from one-size-fits-all thresholds toward individualized glycemic targets and treatment protocols. Future research should develop adaptive algorithms that consider a patient's age, lifestyle, comorbidities, and historical response to treatment [2][16]. This personalization could enable more precise interventions, reducing both hyperglycemic and hypoglycemic events through real-time adjustments.

b) Advanced Noninvasive Detection and Personalized Interventions: Noninvasive detection methods, when coupled with personalized, data-driven approaches, can significantly improve predictive accuracy and facilitate early intervention [24]. By integrating multi-modal data, these systems can identify subtle physiological changes indicative of impending glycemic events, prompting timely and tailored treatment adjustments. Such approaches could transform reactive diabetes management into a proactive, preventive model.

c) Integration with Electronic Health Records (EHRs) and Clinical Decision Support Systems (CDSS): The clinical utility of wearable monitoring systems can be greatly enhanced by their integration with EHRs and CDSS. Future research should focus on establishing secure, standardized interfaces that enable the seamless flow of real-time sensor data into clinical workflows. This integration would provide clinicians with a comprehensive view of patient health, supporting more informed decision-making and facilitating personalized treatment pathways.

d) Addressing Data Privacy and Ethical Concerns: As wearable technologies evolve, ensuring the privacy and security of patient data becomes increasingly critical. Future studies must also address ethical considerations, including data ownership,

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consent, and transparency in AI decision- making processes. Developing standardized frameworks for data governance and ethical AI deployment is essential for maintaining patient trust and ensuring regulatory compliance.

1. *Visual Summary:* A comprehensive infographic could encapsulate these future research directions by highlighting three core thematic areas ~~is~~ as below:Enhanced AI/ML Models: Focusing on interpretability, robustness, multi-modal data integration, adaptive learning, and cloud-edge computing.
2. Advanced Sensor Technologies: Emphasizing next- generation noninvasive sensors, comprehensive biosensor networks, network scalability, interoperability, and robust cybersecurity measures.
3. Personalized Diabetes Management: Showcasing patient-specific adaptive protocols, integration with EHRs/CDSS, proactive intervention strategies, and robust data privacy frameworks.

I. Discussion

In this section, we critically examine the integration of AI/ML with wearable sensors for diabetes monitoring, compare our findings with the existing body of literature, identify key research gaps, discuss ethical, regulatory, and practical considerations, and evaluate the strengths and limitations of our review.

A.Interpretation of Findings

Our analysis of the literature reveals a multifaceted landscape in which AI/ML technologies are increasingly applied to wearable diabetes monitoring systems. We delineate our findings into three main domains: study designs, the integration of AI/ML with wearable sensors, and clinical implications.

a) *Analysis of Study Designs:* The reviewed studies display considerable methodological diversity, encompassing experimental, observational, review articles, and comparative benchmarking studies. Notably, experimental designs account for approximately 67.8% of the included research, with a primary focus on the development, testing, and validation of predictive AI/ML models for diabetes and blood glucose monitoring. Many of these studies incorporate innovative algorithmic enhancements and non-invasive sensor integrations, which are critical for improving measurement accuracy and clinical usability. However, the heterogeneity across study designs introduces variability that challenges the generalizability of these findings to real-world clinical settings. While controlled experimental studies provide strong internal validity, their applicability across diverse populations and practical environments remains constrained.

b) *Integration of AI/ML with Wearable Sensors:* Current applications of AI/ML in wearable diabetes monitoring are rapidly evolving. The primary emphasis is on advanced predictive modeling techniques and sophisticated ~~analyses~~ Analyses of sensor data, which together aim to enhance the precision of glucose monitoring. A structured synthesis matrix has been developed across studies to systematically capture methodological trends and best practices. This matrix reveals common patterns in data collection and analysis while highlighting the variability in how AI/ML is integrated within different healthcare contexts. In diabetes management, these technologies are specifically tailored to support clinical decision-making by providing real-time insights, which may lead to more timely and personalized interventions.

c) *Clinical Implications and Impact on Diabetes Management:* The transformative potential of integrating AI/ML with wearable sensors is particularly evident in the clinical realm. By delivering accurate and real-time data, these technologies empower clinicians to make better-informed treatment decisions. Continuous monitoring and early detection of complications facilitate the design of individualized treatment regimens, thereby improving patient outcomes and overall quality of care. Nonetheless, despite these advantages, barriers such as high implementation costs and the lack of standardized methodological protocols continue to impede the broad clinical adoption of these innovations.

B.Comparison with Existing Literature

A thorough comparison with prior reviews and studies reveals both consonances and divergences, which are critical for contextualizing our findings.

a) Overview of Previous Reviews and Studies: Previous reviews have consistently underscored the potential of AI/ML technologies in revolutionizing diabetes management by enhancing predictive accuracy and enabling continuous monitoring. Traditional studies have emphasized the role of AI/ML in personalizing treatment plans and ensuring real-time data analysis. Methodologically, earlier research has leveraged systematic reviews, meta-analyses, and scoping reviews that share similarities with our approach. However, these earlier investigations often differed in the selection of AI/ML models, the wearable technologies assessed, and the demographic profiles of study populations.

b) Contrasts in Findings and Approaches: Our review diverges from established literature by giving particular attention to novel algorithmic enhancements and the adoption of non-invasive sensor technologies—~~areas that have been relatively underexplored~~relatively underexplored areas. Such divergence can be attributed to recent technological advancements that have markedly improved both the accuracy and usability of diabetes monitoring systems. Furthermore, our implementation of a synthesis matrix allows for a more nuanced understanding of real-world applications across heterogeneous populations, offering insights that extend beyond the conventional scope of prior reviews.

c) Integration of Multidisciplinary Perspectives: An interdisciplinary approach that incorporates perspectives from technology, clinical practice, and data science has been central to our analysis. This integration has not only enhanced the robustness of our findings but also provided a holistic framework for understanding the multifaceted applications of AI/ML in diabetes monitoring. By synthesizing cross- disciplinary insights, our review identifies both best practices and future research directions that could lead to the development of more robust and generalizable models.

C. Research Gaps and Future Directions

Despite significant progress, our analysis identifies several critical gaps in the current research and suggests promising directions for future inquiry.

a) Identification of Gaps in Current Research: A major limitation observed in the literature is the challenge of implementing real-time predictive analytics. This limitation primarily arises from the complexities involved in integrating AI/ML models with wearable devices in dynamic and variable environments. The inherent variability in sensor data, along with the need for adaptive models that can accommodate real-time fluctuations in patient conditions, further complicates this issue. Additionally, the absence of standardized protocols for data collection and model validation undermines the comparability of results across studies, thereby hindering the establishment of consistent performance benchmarks.

b) Recommendations for Future Research: To address these limitations, we advocate for targeted pilot studies that explore the integration of cutting-edge AI models with wearable sensor data in real-world settings. Controlled experimental designs in clinical environments are also essential to rigorously assess the efficacy and reliability of these models. In parallel, fostering interdisciplinary collaborations among engineers, clinicians, data scientists, and ethicists will be crucial for developing comprehensive solutions that address the technical, clinical, and ethical dimensions of AI/ML applications.

c) Emerging Technologies and Innovations: Looking ahead, the integration of emerging technologies such as edge computing, advanced Internet of Things (IoT) frameworks, and blockchain for enhanced data security represents a promising avenue for overcoming current challenges. These innovations could lead to improved data processing speeds, better data integrity, and more scalable AI/ML applications, ultimately driving further improvements in diabetes care and patient outcomes.

D. Ethical, Regulatory, and Practical Considerations

The integration of AI/ML in wearable diabetes monitoring raises several ethical, regulatory, and practical issues that warrant careful consideration.

a) Ethical Considerations: Ensuring the privacy and security of patient data is paramount, particularly as wearable technologies become more sophisticated. Key ethical concerns include data ownership, informed consent, and the transparency of AI decision-making processes. Furthermore, the potential for AI algorithms to propagate existing biases— especially when training datasets lack sufficient demographic diversity—raises significant concerns about equitable healthcare delivery. ~~It is imperative that these technologies ar~~These technologies must be designed with mechanisms to mitigate bias and protect patient autonomy and trust.

b) Regulatory Challenges: The current regulatory landscape for AI/ML and wearable health technologies remains in flux. Existing frameworks often do not fully address the unique challenges presented by these technologies, such as ensuring algorithmic transparency and ~~implementing~~ Implementing continuous monitoring mechanisms. There is a pressing need for comprehensive regulatory guidelines that standardize data collection and model validation protocols, thereby ensuring the safe and ethical integration of AI/ML applications into clinical practice.

c) Practical Implementation Barriers: In addition to ethical and regulatory issues, practical barriers such as interoperability, data management, and infrastructure constraints pose significant challenges. The seamless exchange of data across different devices and systems, efficient handling of large volumes of sensor data, and the establishment of robust network scalability and cybersecurity measures are essential for the successful deployment of these technologies. Strategies to overcome these obstacles include enhancing device interoperability, implementing advanced cybersecurity protocols, and encouraging interdisciplinary collaborations to develop integrated technical solutions.

E.Strengths and Limitations of the Review

Our review exhibits several methodological strengths while also acknowledging certain limitations and potential sources of bias.

a) Methodological Strengths: A major strength of this review is its comprehensive and systematic search strategy, which facilitated the inclusion of a wide range of studies that address diverse AI/ML applications in wearable health monitoring for diabetes. The clearly defined inclusion criteria, coupled with robust analytical methods, allowed for an in-depth synthesis of the current state of research. Moreover, our interdisciplinary approach—integrating insights from technology, clinical practice, and data science—enhances the overall rigor of the analysis. The incorporation of diverse data sources further bolsters the validity and generalizability of our findings.

b) Limitations and Potential Biases: Despite its strengths, the review is not without limitations. The significant heterogeneity among the included studies—in terms of sample sizes, research designs, and measurement techniques—complicates the synthesis of findings and may limit the generalizability of our conclusions. Additionally, publication bias remains a concern, as studies with positive findings are more likely to be published. Language limitations may also have resulted in the exclusion of relevant studies published in non-English languages. Finally, the rapid evolution of AI/ML technologies necessitates ongoing updates to the review, as new developments may quickly render some findings obsolete.

c) Recommendations for Future Reviews: To enhance future research, we recommend the adoption of standardized data extraction protocols to ensure consistency and comparability across studies. Furthermore, expanding the scope to include grey literature and international studies would provide a more comprehensive view of the global landscape of AI/ML applications in wearable health monitoring for diabetes. These steps are essential for addressing the current review's limitations and for advancing the field ~~in a robust and systematic manner~~robustly and systematically.

CONCLUSION

This section synthesizes the key findings of the study, discusses the multifaceted implications for clinical practice, technological innovation, policy-making, and future research, and concludes with reflections on the transformative potential of AI/ML-enhanced wearable technologies in diabetes management.

A. Summary of Key Findings

1) Recap of Research Scope and Objectives

- **Study Focus:** The primary objective of this study was to investigate the integration of Artificial Intelligence (AI) and Machine Learning (ML) technologies with wearable devices for diabetes management. The aim was to enhance the precision and effectiveness of monitoring and managing diabetes through advanced predictive modeling and real-time data analytics.
- **Methodological Approaches:** The research synthesized evidence from a diverse array of methodological approaches, including experimental designs, observational studies, systematic reviews, and comparative benchmarking analyses. Notably, experimental designs were extensively employed to develop and validate robust AI/ML models specifically tailored for diabetes monitoring.

2) Major Insights and Outcomes

- **Enhanced Monitoring and Predictive Accuracy:** The deployment of AI/ML algorithms has markedly improved the accuracy of diabetes monitoring. Through sophisticated sensor data analysis, these algorithms facilitate precise glucose level tracking and advanced predictive analytics, thereby enriching clinical decision-making.
- **Improved Patient Outcomes:** Empirical findings indicate that AI/ML-enhanced wearable devices enable early detection of complications and support personalized care adjustments. This tailored approach contributes to significantly improved patient outcomes and elevates the overall quality of diabetes management.
- **Critical Role of Wearable Devices:** Wearable technologies are central to continuous health data collection, establishing dynamic, real-time feedback loops. This continuous monitoring empowers clinicians with immediate, actionable insights that inform personalized interventions.

3) Breadth of Research and Identified Gaps

- **Interdisciplinary Scope:** The research spans multiple disciplines, including bioengineering, data science, and clinical medicine, underscoring the multifaceted nature of integrating AI/ML with wearable health technologies.
- **Identified Research Gaps:** Despite promising advancements, significant gaps persist. These include the need for larger sample sizes, comprehensive long-term efficacy studies, and improved integration with existing healthcare systems to ensure the generalizability and scalability of the findings.
- **Limitations of Current AI/ML Models:** The study highlights critical limitations such as data privacy issues, lack of algorithm transparency, and potential biases in model outputs. Addressing these concerns is pivotal for the broader clinical acceptance of AI- driven wearable technologies.

B. Implications for Practice, Policy, and Research

1) Implications for Clinical Practice

- **Enhanced Monitoring and Early Intervention:** The real-time data provided by wearable devices facilitates proactive clinical interventions. This capability is critical for early complication detection and for initiating timely, preventative measures.
- **Personalized Treatment Plans:** Leveraging individualized data trends and predictive analytics enables the development of tailored treatment plans that address the unique needs of each patient, thereby optimizing therapeutic outcomes.
- **Integration with Telemedicine:** The convergence of wearable technology and telemedicine expands the reach of healthcare services, particularly in remote or underserved areas, by enabling continuous patient monitoring and remote consultations.

2) Implications for Technological Advancements

- **Innovation in Sensor and Device Technologies:** There is a pronounced need for the development of more accurate and less invasive sensors. Advances in sensor technology will not only enhance user experience but also improve the reliability and precision of the collected data.
- **Enhancements in AI/ML Algorithms:** Future research should focus on refining AI/ML algorithms to boost their predictive accuracy while minimizing the incidence of false positives and negatives. Enhancing these algorithms is essential for bolstering clinical trust and utility.
- **Data Integration and Interoperability:** The creation of integrated platforms that seamlessly consolidate wearable data with electronic health records (EHRs) is imperative. Such integration will enable a holistic view of patient health and support more informed clinical decision-making.

3) Implications for Policy-Making

- **Regulatory Frameworks and Standards:** The establishment of comprehensive regulatory frameworks and standardized protocols for data security, privacy, and device accuracy is crucial. These measures will ensure the ethical and safe deployment of wearable health technologies in clinical practice.
- **Funding and Investment:** Enhanced investment from both governmental and private sectors is necessary to support ongoing research and the commercialization of AI/ML-enhanced wearable technologies. Adequate funding is a critical driver for accelerating innovation and clinical adoption.

4) **Ethical Considerations and Patient Rights:** Addressing ethical issues—such as data usage, informed consent, and the implications of automated decision-making—is paramount. Transparent practices and strict adherence to ethical guidelines will foster trust and facilitate the acceptance of these advanced technologies.

5) Implications for Future Research

- **Interdisciplinary Collaborations:** Future research should foster collaborative partnerships among clinicians, engineers, data scientists, and policymakers. These interdisciplinary efforts are vital for addressing the complex challenges associated with integrating AI/ML with wearable technologies.
- **Longitudinal and Large-Scale Studies:** Conducting long-term and large-scale studies is essential to verify the sustained efficacy and safety of AI/ML-enhanced wearables. Robust empirical evidence from such studies will underpin broader clinical adoption.
- **Exploration of Novel Data Streams:** Investigating additional data sources—such as environmental influences and lifestyle metrics—can further refine predictive models. A comprehensive approach to data integration will lead to more robust and accurate health monitoring systems.

C. Final Remarks

1) Synthesis of the Study's Impact

- **Transformative Potential:** The study underscores the revolutionary impact of integrating AI/ML with wearable devices in diabetes management. By providing real-time, precise data, these technologies enable enhanced clinical decision-making and substantially improve patient care.
- **Convergence of Technology and Healthcare:** The integration of cutting-edge technology with clinical practice is anticipated to significantly elevate patient outcomes. Continuous monitoring coupled with early complication detection facilitates the development of highly individualized treatment regimens, ultimately improving the overall quality of care.

2) Call to Action for Further Research

- **Urgency for Continued Innovation:** There is an imperative need for sustained innovation and increased research investment to overcome current challenges, such as hardware-software integration and data interoperability. Addressing these issues is critical for the effective real-world application of these technologies.
- **Encouragement for Collaborative Projects:** Stakeholders are urged to pursue interdisciplinary collaborative projects that align technological advancements with clinical imperatives. Such endeavours are essential to drive further innovation and address the multifaceted challenges inherent in modern diabetes management.

3) Vision for the Future

- **Optimistic Outlook:** The future integration of AI/ML in diabetes management holds immense promise. These technologies are poised to empower patients with advanced self-management tools while equipping healthcare providers with timely, actionable insights.
- **Sustained Research and Collaboration:**

Continuous research and collaborative efforts will be pivotal in driving the next wave of innovations in personalized healthcare. By rigorously addressing ethical considerations and ensuring robust data security, the field can cultivate widespread trust and acceptance of AI/ML-enhanced wearable technologies, ultimately transforming healthcare delivery.

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