

Towards an AI-assisted T1DM Data Analysis Pipeline

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Abstract

This paper presents a data-driven approach for analyzing diabetes-related data, with a particular focus on pediatric patients with Type 1 Diabetes Mellitus (T1DM). We propose a methodology that integrates data from multiple wearable devices to examine the impact of physical activity and the use of medical technologies on patient health. Our approach utilizes the JupyterHub framework to combine data analytics and artificial intelligence (AI) within a secure, privacy-preserving environment. We conducted a preliminary case study based on data collected during a pediatric diabetes camp held in September 2024. The analysis employs advanced visualization tools (Plotly and hvPlot) and cross-correlation techniques to uncover patterns between physiological and glycemic parameters. The proposed system enables healthcare professionals to receive graphical and textual insights through an AI assistant, ultimately supporting more informed clinical decision-making and enhancing the quality of care for diabetic children.

1. Introduction

1.1. Background and Motivation

Managing Type 1 Diabetes Mellitus (T1DM) in pediatric patients presents significant challenges, particularly in monitoring and treatment. A major obstacle is the integration of data from diverse medical sources to form a holistic understanding of a patient's condition. Children with diabetes must monitor not only blood glucose levels but also factors such as diet, physical activity, and sleep on a daily basis. Although physical activity has demonstrated positive effects on glycemic control and overall well-being, its optimal implementation in pediatric care remains underexplored. Traditional monitoring systems are often inadequate for capturing multi-dimensional insights from wearable and medical devices. Furthermore, the high volume and complexity of data generated by technologies like insulin pumps and wearable monitors can overwhelm healthcare providers. As a result, deriving actionable, personalized insights without advanced analytical tools becomes difficult, limiting effective treatment optimization. This research investigates whether it is feasible to design a personalized assistant that aids diabetologists in interpreting heterogeneous data streams from various wearable devices. A secondary goal is to determine whether this can be achieved while preserving patient privacy—specifically, by avoiding reliance on cloud-based solutions for data processing and analysis.

1.2. Proposed Approach

To address these challenges, we introduce a methodological framework that integrates physical activity data and glycemic monitoring through a combination of traditional data analysis and artificial intelligence, with a focus on locally deployable learning models.

Methodology

Specifically, the tasks to be accomplished are as follows:

1. Data integration - combine and preprocess collected data ensuring consistency and compatibility for further analysis,



2. Data analysis - evaluate the relationship between physical activity levels and blood glucose fluctuations to determine the impact of exercise in diabetic patients,
3. Support system development - develop an AI-driven support system that will be able to assist medical specialists by providing real-time insights, graphical representations, and textual explanations based on data analysis,
4. Evaluation of Machine Learning methods - compare the effectiveness of traditional data analysis techniques with AI-driven approaches, assessing the accuracy, usability and practical value of the provided results.

1.3. Novel Contribution

The novelty of our work lies in its focus on pediatric diabetes, where the unique challenges of managing fluctuating glucose levels, growth-related metabolic changes, and physical activity patterns demand tailored solutions. Furthermore, the integration of local AI-enabled platforms with wearable technologies not only enhances glycemic control in diabetic patients, but also assists healthcare professionals by offering evidence-based recommendations through an intuitive and user-friendly chatbot interface.

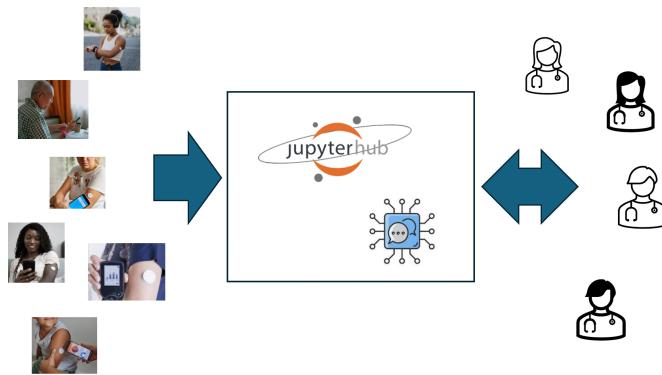


Figure 1: Jupyter Hub used to centralized data acquistion and interaction between AI agents and professionals.

1.4. Plan of the paper.

In Section 2 we discuss related work. In Section 3 we present our case-study involving multi-modal sensor data. In Section 4 we describe the data processing pipeline designed for our case-study that involves data fusion, analysis, and visualization and the results obtained with classifical statistical methods. In Section 6 we present preliminary ideas and experiments related toward th integration of an AI agents based on SLM and RAG customized on our domain. In Section 7 we address limitations, conclusions and future work.

2. Related work

During the last decades, we were observing a huge progress both in informatics and medicine spheres. They became inseparable parts of each other and one of the most vital benefits of such an alliance is the significant growth of life expectancy. Artificial Intelligence (AI) is nowadays actively used to support the research on Type 1 Diabetes. According to [1], effective adoption of AI requires profound research, information security, collaboration across disciplines, and a commitment to patient-centered approaches. AI has been identified as a transformative force across eight key domains in diabetes care: 1) Diabetes Management and Treatment, 2) Diagnostic and Imaging Technologies, 3) Health Monitoring Systems, 4) Developing Predictive Models, 5) Public Health Interventions, 6) Lifestyle and Dietary Management, 7) Enhancing Clinical Decision-Making, and 8) Patient Engagement and

Self-Management. Each domain showcases AI's potential to revolutionize care, from personalizing treatment plans and improving diagnostic accuracy to enhancing patient engagement and predictive healthcare. In [2] the authors provide a detailed review of 77 research papers showing how AI can be applied to enhance and personalize diabetes treatment. Two key trends of using AI were pointed out: therapy personalization and therapeutic algorithm optimization, while also some lack of interoperability and multi-modal database analysis was detected, which indicates that existing studies predominantly focus on single data sources rather than integrating diverse datasets to provide a comprehensive understanding of diabetes management. This limitation reduces the potential for AI models to capture complex interactions between physiological, behavioral, and clinical factors, ultimately restricting their ability to generate precise and personalized therapeutic recommendations. In [3] the authors highlight the widespread adoption of supervised learning models, such as Random Forest and Support Vector Machines (SVM), which consistently demonstrate high accuracy and reliability in predicting the diabetes risk. Ensemble learning methods, particularly Gradient Boosting, emerged as superior techniques for predictive performance, while deep learning models, including Convolutional Neural Networks (CNNs) and Recurrent Neural Networks (RNNs), proved effective in analyzing unstructured data such as medical images and time-series glucose data. These advances have been showcased in various conferences, including the Advanced Technologies and Treatments for Diabetes (ATTD) 2025 conference, where AI-driven platforms demonstrated remarkable potential in real-time diabetes management. AI systems that analyze the vast amounts of data produced by wearable devices and medical devices have also contributed to improved decision-making and better clinical outcomes [4]. In the medical domain, insulin pumps, such as those developed by Medtronic, have revolutionized the treatment of diabetes. These devices provide continuous, controlled insulin delivery, reducing the need for frequent injections and improving glycemic control. Medtronic's insulin pumps, equipped with advanced algorithms and sensors, enable dynamic adjustments to insulin delivery based on real-time glucose measurements, significantly enhancing the precision of diabetes management [5]. Medtronic employs both AI-based and traditional control algorithms to optimize insulin dosing. Non-AI-based algorithms, such as proportional-integral-derivative (PID) controllers and model predictive control (MPC), rely on mathematical models and predefined rules to regulate insulin delivery. In contrast, AI-driven algorithms, including machine learning-based adaptation systems, leverage historical and real-time data to predict glucose fluctuations and personalize insulin administration more effectively. For instance, The MiniMed™ 780G system features an algorithm that automatically adjusts basal insulin delivery and provides auto-correction boluses based on continuous glucose monitoring data, aiming to maintain glucose levels within a target range [6]. Additionally, Medtronic has introduced a smart insulin pen that integrates glucose sensor data, utilizing AI to assist patients with type 1 diabetes who rely on multiple daily injections [7]. On the other hand, wearable devices such as Comftech's Howdy Senior textile devices could expand the scope of diabetes care by incorporating physical activity monitoring into routine management. These devices track key physiological parameters, providing real-time data that can help assess the impact of physical activity on blood glucose levels. The integration of these wearables with AI-based platforms offers a holistic approach to diabetes care, allowing healthcare providers to tailor insulin delivery and lifestyle recommendations based on comprehensive data from both medical and activity-monitoring devices [8]. Numerous studies have demonstrated the critical role of physical activity in managing diabetes, particularly in children and adolescents. Exercise helps improve insulin sensitivity, lowers blood glucose levels, and enhances cardiovascular health, reducing the risk of diabetes-related complications. A systematic review by Sun Z. confirmed that regular and multi-component physical activity improves glycemic control, reduces HbA1c levels and allows to delay cognitive decline in individuals with diabetes [9]. Moreover, studies have highlighted the positive effects of exercise on the mental health, quality of life and a general well-being of diabetic patients, especially in the pediatric population [10]. The interaction between insulin therapy and physical activity has been a subject of intense research, with recent studies showing that wearable devices can help optimize exercise plans by providing personalized feedback based on real-time glucose monitoring. These AI-driven technologies enable caregivers and patients to adjust insulin doses dynamically to ensure safe participation in physical activities while avoiding hypoglycemia or hyperglycemia [11].

This study focuses specifically on pediatric diabetes, an area where managing blood glucose levels can be particularly challenging. Children and adolescents with diabetes experience unique physiological and behavioral factors that complicate glycemic control, including varying levels of physical activity, growth spurts, and psychosocial influences. The integration of advanced AI algorithms, insulin pumps, and wearable devices offers a promising solution to these challenges, allowing for continuous monitoring and personalized treatment plans tailored to the specific needs of pediatric patients.

3. Case Study: Glooko Platform and Howdy Senior Wearable Data

3.1. Data Hub

In our project, we leverage JupyterHub as a central platform for acquiring, processing, and analyzing wearable data in a secure environment. This approach enables collaboration among researchers and clinicians while ensuring that sensitive health data remains within institutional boundaries. The Jupyter ecosystem (Hub, Lab and Notebook) [12] provides an interactive computing environment that supports the documentation, analysis, and visualization of complex datasets. Jupyter Notebooks are particularly well-suited for implementing the Findable, Accessible, Interoperable, and Reusable (FAIR) principles [13]. JupyterHub extends these capabilities to multiple users, allowing centralized management of computational notebooks, authentication through OAuth, and customized virtual environments for each user.

Our JupyterHub instance is deployed on a virtual machine hosted by the joint laboratory of the Gaslini Pediatric Hospital and our university department. The system integrates data collected from two sources: insulin pumps and glucose monitors, and a textile wearable developed by ComfTech. These datasets are initially stored on proprietary cloud platforms managed by the device manufacturers. We redirect these data to the JupyterHub instance, ensuring local control and privacy. Figure 1 illustrates

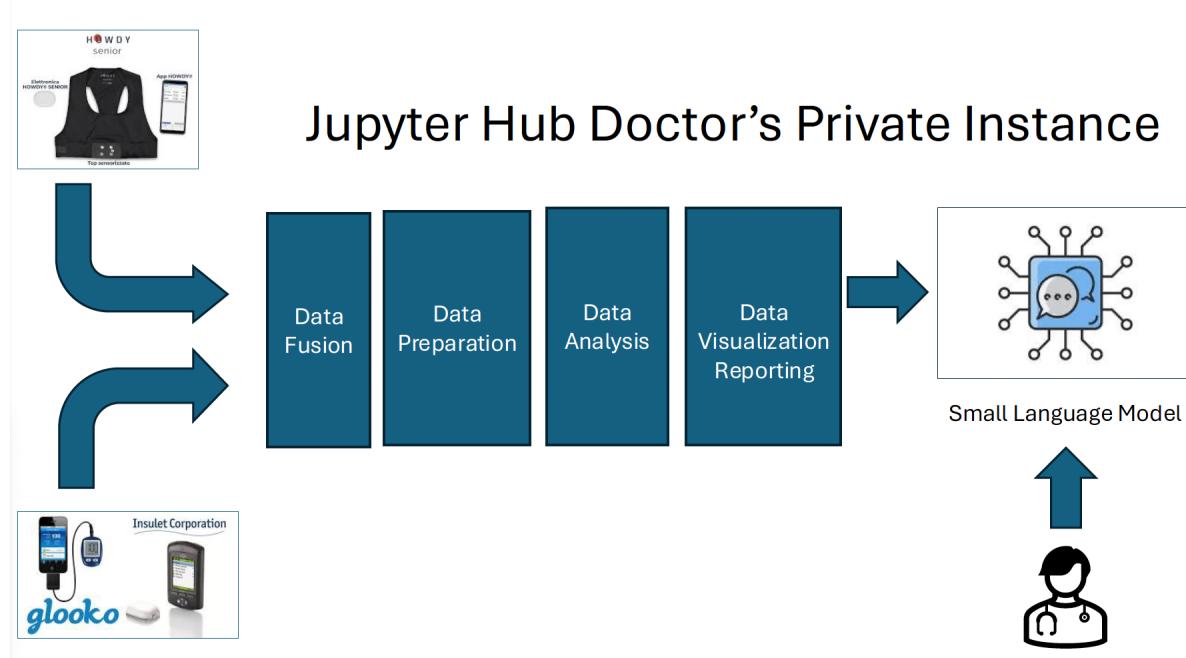


Figure 2: The internal architecture of an instance of our Jupyter Hub platform

the system architecture: JupyterHub provides pre-configured environments for data ingestion, fusion, and analysis using the Python ecosystem. The platform allows the generation of analytical reports, which serve as inputs for AI-based assistants. These assistants are designed to support diabetologists by offering structured insights, thereby reducing the cognitive load of interpreting raw data. JupyterLab

also allows professionals to visualize both raw and aggregated data, giving them greater flexibility in exploring patterns related to glycemic control and physical activity.

3.2. Data Collection

The data used in this study were collected through a collaborative effort between the Gaslini Pediatric Hospital and Comftech, a non-participatory spin-off of the Polytechnic University of Milan that specializes in wearable monitoring devices [14]. To facilitate data acquisition, a pediatric diabetes summer camp was organized by Gaslini Hospital in Sarzana, Italy. The primary goal was to monitor the physiological and metabolic responses of five pediatric patients with T1DM during daily physical activities. Throughout the camp, all participants were supervised by medical staff and wore two types of devices: insulin pumps with continuous glucose monitors (CGMs) and Comftech's Howdy Senior sensorized garments. These garments measure multiple physiological parameters such as heart rate variability, ECG, respiration rate, stress index, and movement [15].

Post-camp, the insulin-related data were downloaded from the Glooko platform, while physical activity data were obtained from Comftech's proprietary system. Glooko is a diabetes management platform designed to facilitate the visualization, interpretation, and management of diabetes-related data from medical devices. A screenshot of the Glooko interface is shown in Figure 3.

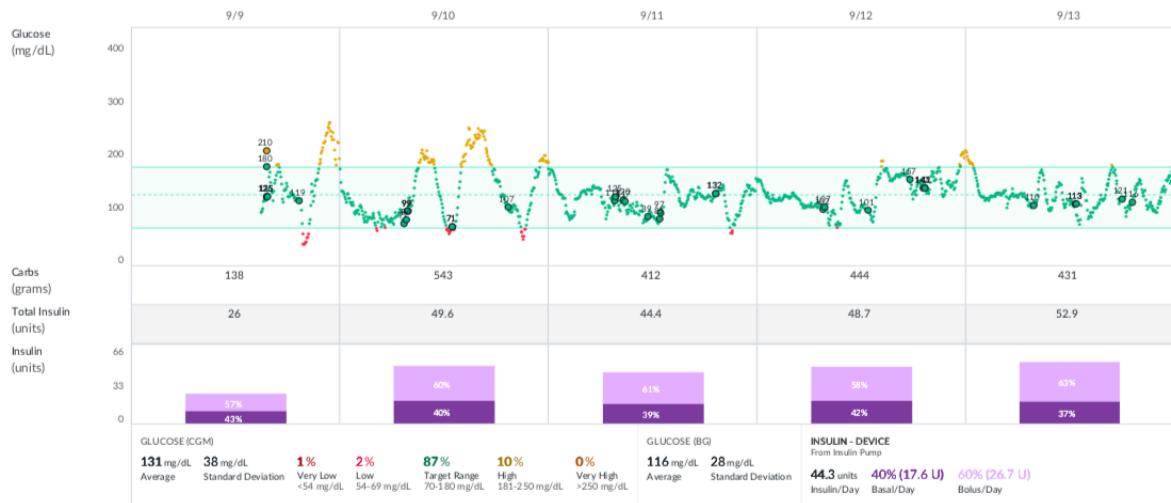


Figure 3: Glooko interface

The interface displays the data over a five-day period, including continuous glucose monitoring (CGM), carbohydrate intake, and insulin levels.

All data were anonymized and securely stored in a local repository for further analysis. For this case study, we focus on the dataset from a single anonymized patient to demonstrate our methodology.

3.3. Howdy Senior Dataset

Our dataset contains multi-modal time-series data captured over five days. Data formats included CSV, Excel, and JSON, with each device contributing distinct physiological and metabolic metrics. These datasets were organized for preprocessing and analysis within our JupyterHub environment. The dataset includes different time-series data on different physiological measurements. These parameters, recorded with specific timestamps, are structured as follows: Heart Rate, Breath Rate, Movement. The data encompasses the following fields: date, value, measure type, and timestamp. The dataset is structured in a tabular format with 165,138 entries and 4 columns, with each entry corresponding to a specific timestamp and the corresponding measurement values.

Continuous heart rate variability (HRV). The continuous HRV data includes the HRV score, stress index, and high-frequency (HF) power. The data consists of date, value, measure type, and timestamp fields, with a total of 447 records. Certain physiological signals were not directly available for download from the platform and were instead provided as raw data by the Comftech administrator in .csv and .json formats. These additional signals include:

ECG trace (tacogram). The ECG data consists of single-lead ECG traces sampled at a rate of 128 Hz. The values are expressed in millivolts (mV). This dataset provides continuous physiological data over a substantial period, with 1,200,256 data points captured.

Respiratory signal. The respiratory data was acquired at a sampling rate of 13 Hz, with the values expressed in analog-to-digital converter (ADC) levels. This data captures respiratory activity over time, represented by 129,766 entries and three columns (date, value, and measure type).

Acceleration signals The dataset includes triaxial accelerometer signals, capturing lateral (X-axis), vertical (Y-axis), and antero-posterior (Z-axis) accelerations. These signals were sampled at 25 Hz, and the values are expressed in gravitational units (g). There are 229,300 entries across three axes.

3.4. Glooko Dataset.

The data from the Glooko platform was downloaded in .csv format. The dataset includes various parameters related to insulin delivery, blood glucose monitoring, and alarms/events. These data are structured as follows:

Insulin data The insulin-related data includes two main categories: basal and bolus insulin delivery, as well as overall insulin usage. The dataset provides information about the type of insulin used, the amount administered, and related temporal variables. Basal Insulin Data captures information on basal insulin delivery, which controls overall blood glucose levels, including the date and time of administration, type of insulin used, duration (in minutes), percentage of dosage, frequency, total insulin administered, and serial number. The dataset consists of 466 records. Bolus Insulin Data includes records on insulin bolus injections, which manages spikes caused by eating, with fields for the date and time, type of insulin, pre-meal blood glucose level (in mg/dL), carbohydrate consumption (in grams), carbohydrate-to-insulin ratio, total insulin administered, initial bolus delivery, extended bolus delivery, and serial number. This dataset contains 37 entries. Total Insulin Data includes information on the total bolus and basal insulin administered, as well as the overall insulin usage over time. It consists of six records with date, time, and the corresponding insulin values.

The blood glucose data This data contains entries for manually recorded blood glucose levels. The dataset includes the date and time of each measurement, the glucose value (in mg/dL), and whether the reading was taken manually. This dataset contains 32 records.

Continuous Glucose Monitoring (CGM) Data The CGM data records continuous glucose measurements obtained through a CGM system. The dataset includes the date and time of each glucose reading, the corresponding glucose value (in mg/dL), and the serial number of the device. This dataset comprises 1,067 entries. In summary, the dataset provides a wide and diverse range of both physiological and diabetes related measures, all of which were collected using various sensors mounted on the subject. The comprehensive nature of the dataset enables robust analysis and modeling of the subject's physiological states over time.

4. Data Processing Pipeline

Raw datasets were not immediately compatible with analytical workflows in JupyterLab. To address this, we employed a preprocessing pipeline using the "Amphi" tool, which supports interaction with CSV files and allows for the construction of custom data workflows.

First, the datasets were separated into nine measurement categories: breath frequency, step count, heart rate, movement index, stress index, heart rate variability, basal insulin, bolus insulin, and CGM data. Each category was processed independently to ensure consistency in formatting and timestamps. Figure 4 illustrates the pipeline used to preprocess the basal and bolus data. The process begins by

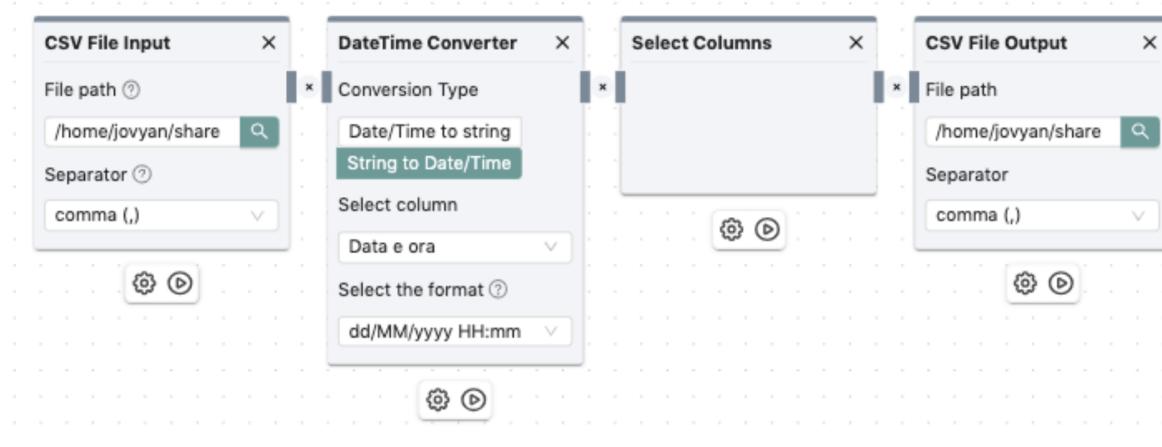


Figure 4: Pipeline for preprocessing basal and bolus data

importing the original .csv file. The first step in the pipeline involves converting the date field from a string format to a Date/Time format. The "Select Columns" block is then employed to retain only the relevant columns—those containing bolus/basal data and corresponding timestamps. In the "Rename Columns" block, the selected columns are renamed for clarity and convenience. Finally, the modified .csv file, containing the preprocessed measurement data, is saved. This pipeline is subsequently applied to the CGM data. In contrast, the preprocessing algorithm for physical data derived from the Comftech

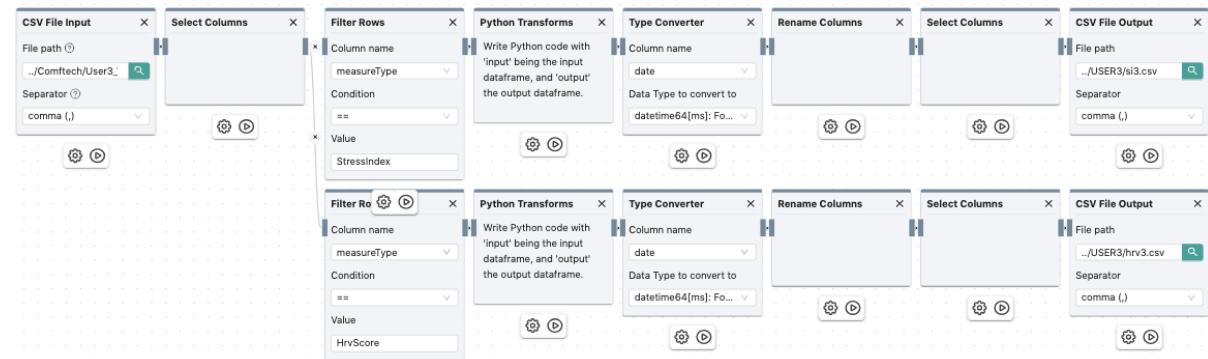


Figure 5: Pipeline for preprocessing physiological data

platform requires adjustments (Figure 5). For instance, when processing the stress index and heart rate variability measures, the "Filter Rows" block isolates the required parameters from the full dataset.

The "Python Transforms" block is then used to convert the date column from string format into Date/Time format to ensure consistency in date formatting across the dataset. This procedure is repeated for the remaining six parameters. Upon completion of these steps within the Amphi environment, the nine preprocessed .csv files are transferred to an .ipynb notebook for additional processing. More

specifically, the columns in each file were reordered to ensure that the date field appears first. Duplicate entries in the “Breath Frequency” file were removed due to the detection of repeated values. Furthermore, in the “Bolus” and “Basal” files, periods in the data were replaced with commas, and the data type was converted to “float64” for consistency. This pipeline resulted in a clean, structured dataset composed of nine CSV files, ready for detailed time-series analysis and machine learning tasks.

5. Data Analysis

This section presents the outcomes of a detailed analysis of the processed dataset, conducted in the Jupyter Notebook environment using Python. We employed a range of data visualization and statistical tools to identify correlations and temporal trends within the physiological and glycemic data. Interactive visualizations were created using Plotly and hvPlot, while cross-correlation and correlation matrix techniques were used to explore interdependencies among variables.

To begin, all nine preprocessed CSV files were loaded into the notebook. A multi-axis scatter plot was generated using Plotly to visualize selected variables—such as glycemia, insulin delivery, heart rate variability (HRV), and stress index—across the five-day camp period. Each data point on the graph is interactive, displaying the associated value, date, and time. The plot includes four drop-down selectors for the axes and a checkbox to toggle between viewing the entire dataset or specific time intervals.

For example, in one configuration (Figure 6), glycemia, insulin levels, and movement index are

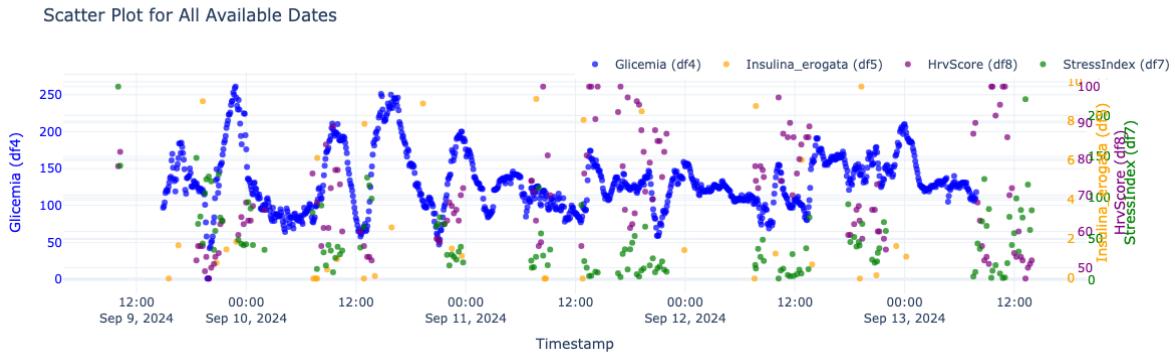


Figure 6: Visualization of the complete dataset

visualized together. Glycemia levels (blue points) display a cyclical pattern, likely reflecting daily fluctuations associated with meals, activity, and insulin injections. The corresponding insulin doses (orange points) indicate reactive administration in response to glycemic peaks. The movement index (purple points) suggests a possible relationship between physical activity and blood glucose regulation. The plot is equipped with five interactive widgets: four drop-down menus for selecting the axes and one checkbox for toggling between viewing data for all days or specific days. Users also have the option to exclude axes if fewer parameters need to be visualized.

As an example, the plot can display glycemia alongside administered insulin and movement index (Figure 7). The glycemia values, represented by blue points, exhibit a cyclic pattern with peaks and troughs, suggesting diurnal variations in blood glucose levels. It ranges between 0 and 261 units. Periods of increased glycemic values are interspersed with lower readings, corresponding to physiological or behavioral rhythms, such as meals or insulin administration. The ergogated insulin in orange points suggest discrete delivery of insulin in response to elevated glycemia values. The movement index in purple points displays cyclical fluctuations, with periods of higher activity potentially coinciding with glycemic trends. This could indicate a relationship between physical activity and glycemic control.

To enable more flexible visual exploration, a merged dataset was created using timestamp alignment (nearest match method with 1-second resolution). New categorical columns were added to this dataset to represent different glycemia and movement levels (e.g., low, normal, high). This merged data was

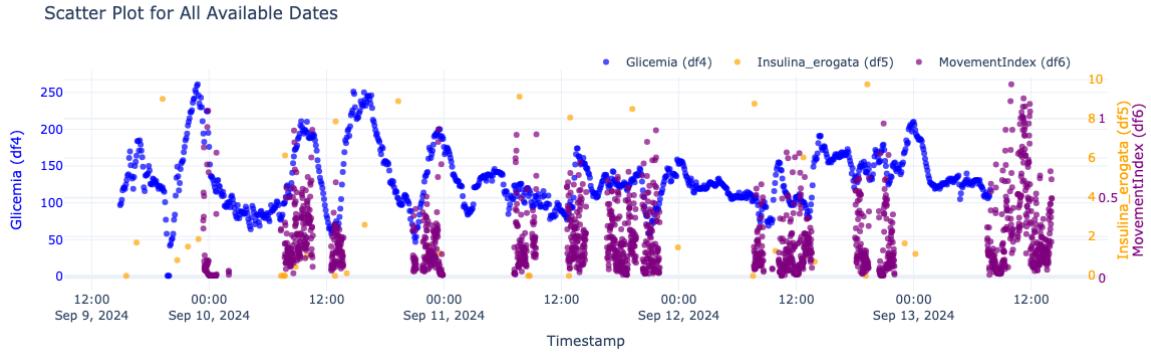


Figure 7: Scatter plot of three measures

visualized using hvPlot, which provides dynamic plot types tailored for time-series analysis. The

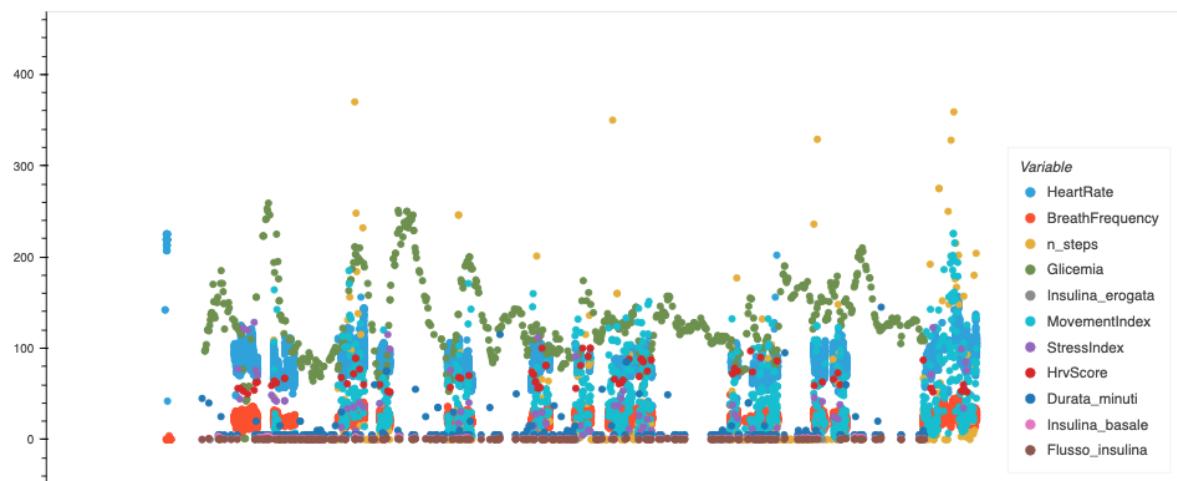


Figure 8: hvPlot scatter plot

hvPlot scatter plot, visualizing all merged measures, is shown in Figure 8. This visualization method is particularly advantageous due to its versatility, allowing data to be explored through various plot types.

We then applied cross-correlation analysis to examine time-lagged relationships between variables. The merged dataset was split into parameters which were then visualized separately from each other.

The plot in Fig. 9 represents the cross-correlation between HeartRate and MovementIndex over a range of time lags, with a maximum lag of 150. Cross-correlation measures the similarity between two signals as one is shifted relative to the other, providing information on potential time-dependent relationships between variables.

Fig. 10 shows the cross-correlation between heart rate and glycemia over a range of time lags reveals the highest positive correlation at a lag of 123, indicating that an increase in heart rate is followed by a corresponding increase in glycemia approximately 123 time units later. In contrast, the strongest negative correlation occurs with a delay of 8, suggesting that an increase in heart rate precedes a decrease in glycemia within this short time frame. The correlation pattern fluctuates over different lags, with a significant negative correlation around lag 0, which may indicate an immediate inverse relationship between changes in heart rate and glycemia.

In contrast, the plot, which represents the cross-correlation between movement index and glycemia in Fig. 11, exhibits a more erratic pattern. Unlike the structured periodicity observed in the heart rate-glycemia relationship, the correlation between movement and glycemia appears less consistent, with pronounced spikes particularly around lag 0. The presence of positive and negative correlations across

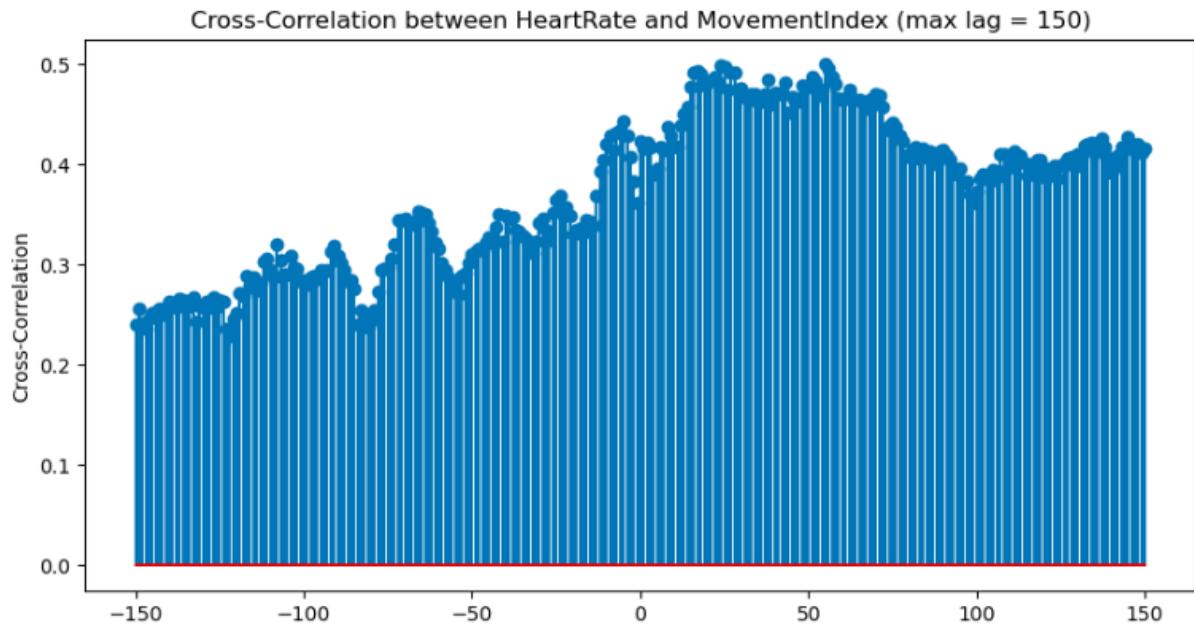


Figure 9: Cross-correlation between heart rate and movement index

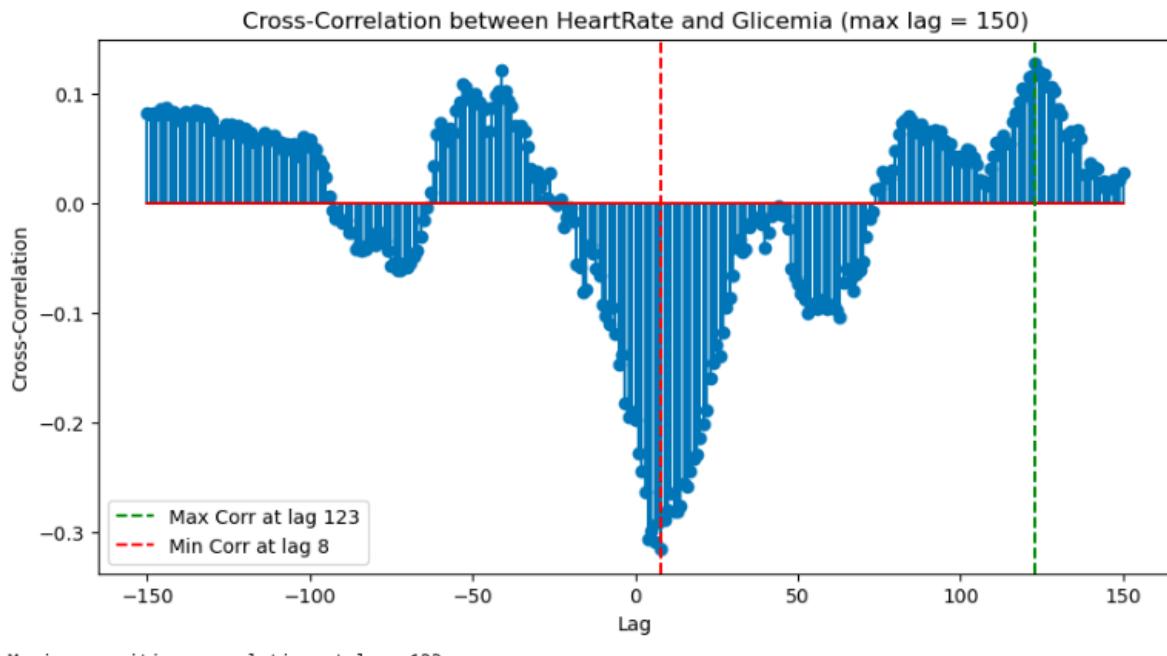


Figure 10: Cross-correlation between heart rate and glycemia

different time lags suggests that the effect of movement on glycemia is influenced by additional factors, such as insulin administration, food intake, and individual physiological responses. The irregular nature of these fluctuations implies that movement alone may not be a reliable predictor of glycemia changes compared to heart rate.

The cross-correlation values are predominantly positive across all lags, indicating that HeartRate and MovementIndex are generally positively correlated. This aligns with the physiological expectation that higher levels of physical activity are associated with an increase in heart rate. The cross-correlation peaks around positive lags (e.g., 50 to 100), suggesting that changes in the MovementIndex tend to

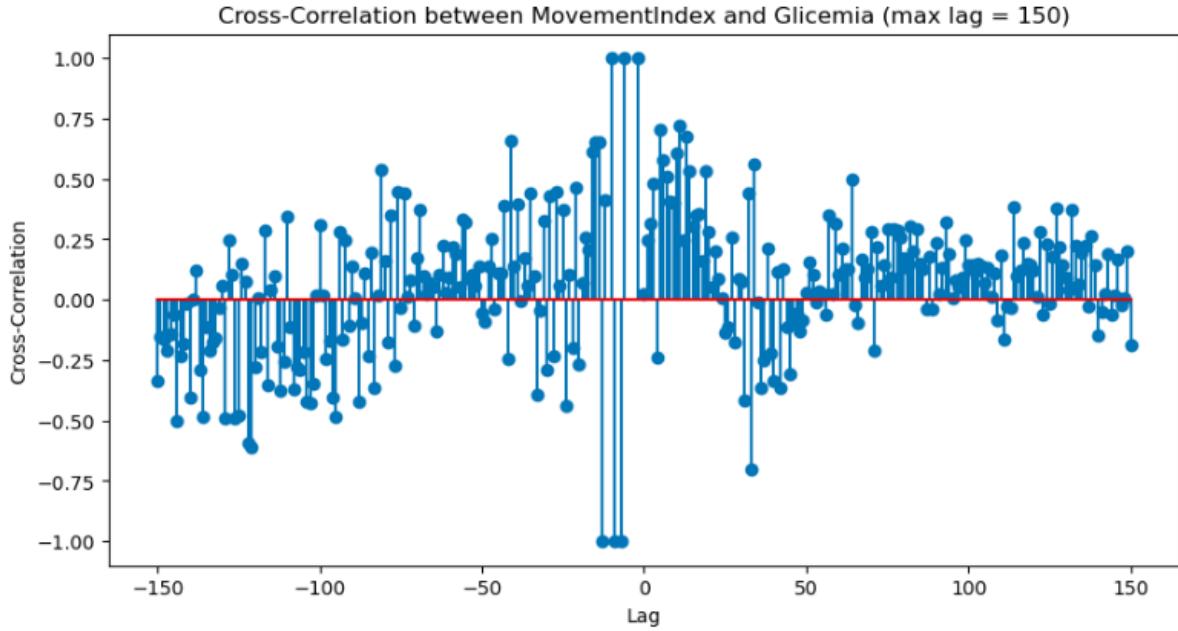


Figure 11: Cross-correlation between movement index and glycemia

precede corresponding changes in HeartRate. This implies that heart rate increases with some delay after physical activity intensifies. The correlation matrix in Fig. 12 represents the relationships between all the variables. The values in the matrix range from -1 to 1. The strongest correlation is observed between Glycemia and Basal Insulin (0.79), highlighting a strong direct relationship. The stress index demonstrates a strong negative correlation with glycemia (-0.72), suggesting that increased stress levels are associated with lower glycemia, potentially due to metabolic changes or increased energy expenditure under stress. Interestingly, movement index has a moderate positive correlation with HRV score (0.67), suggesting that increased movement is associated with improved heart rate variability, which is often considered a marker of better autonomic function. Breathing frequency correlates positively with insulin delivery (0.59), possibly reflecting an association between metabolic demands and respiration. However, its correlation with stress is weak and negative (-0.17), suggesting that stress levels do not directly influence respiratory rate in a significant way.

There is a moderate positive relationship between HeartRate and MovementIndex (0.42), reflecting the physiological response of increased heart rate during physical activity. These insights highlight the potential of integrated multi-modal data to support more personalized, data-driven diabetes care.

6. Preliminary Experiments Towards an AI assistant

In our preliminary experiments towards the creation of an AI-based assistants, we followed an approach based on the combination of Small Language Models (SLMs), specialized embeddings and Retrieval-Augmented Generation (RAG) [16]. SLMs can perform well on standard devices, without requiring large-scale infrastructure and can be seen as a way to make machine intelligence accessible and affordable to anyone. While model compression techniques have enabled the development of smaller models that are more efficient and can maintain competitive performance, both Large Language Models (LLMs) and Small Language Models (SLMs) struggle with answer reliability. Answer reliability refers to a model's ability to provide accurate, current, and verifiable responses that can be related to attested sources. RAG has been proposed to solve the problem of traceability since they can trace the knowledge from which the statement has been generated. Furthermore, RAG combine the generative capabilities of LLMs with information retrieval techniques. This method enhances the model's ability to provide accurate and contextually relevant responses by retrieving information from external knowledge bases. Furthermore,

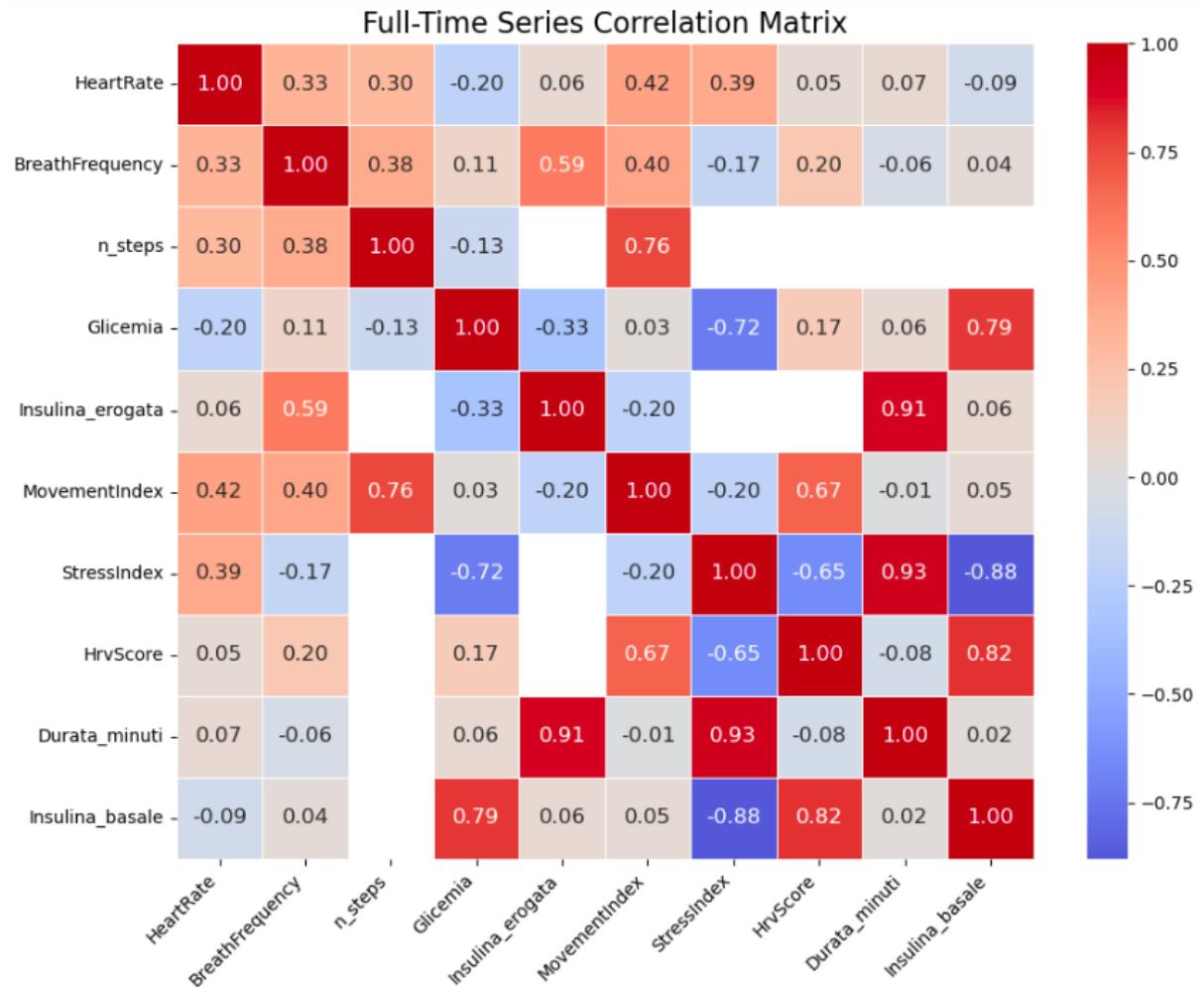


Figure 12: Full-time series correlation matrix

SLMs and RAG can be used to ensure data privacy when working with custom models.

In our setting, first of all we created a documental repository by automatically generating, via ad hoc Python scripts, notebooks with data discussed in the previous section. More precisely, the data encompassed various physiological parameters, including:

- **Heart Rate:** Number of heartbeats per minute over the dataset period (five days);
- **Breath Frequency:** Number of breaths per minute;
- **Insulin Administration:** Total insulin administered during the monitoring period;
- **Blood Glucose Levels (Glicemia):** Concentration of glucose in the blood;
- **Physical Activity (Step Count):** Number of steps taken during the monitoring period;
- **Movement Index:** Movement intensity during the monitoring period;
- **Stress Index:** Stress levels;
- **HRV Score:** Heart Rate Variability (HRV) score reflecting the variation in time intervals between heartbeats;
- **Basal Insulin Administration:** Basal insulin administered.

For this experiment, the knowledge base was exclusively based on the provided biometric data. During system prompting, additional contextual information was given more precisely, the glycemic values were categorized as follows.

- For a healthy person:

- Low level: ≤ 70 ;
- Normal level: 71 - 99;
- High level: >99 .

- For a diabetic patient:
 - Low level: ≤ 69 ;
 - Normal level: 70 - 180;
 - High level: >181 .

The retrieval mechanism was designed to return relevant data for answering queries. Initially, data was formatted as CSV, but this approach resulted in poor retrieval performance. Switching to a more descriptive format, where each measurement was stated in natural language, e.g. “Heart Rate Max Heart Rate 2024-09-09: 232.0, Min Heart Rate 2024-09-09: 42.0, Mean Heart Rate 024-09-09: 90.37208218293951”, improved the retrieval system’s accuracy. We include some example of PDF generated by the resulting notebooks containing max, min and mean values for all parameters for all days of a given (anonymous) user in Fig. We then formulate the list of 8 questions shown in Fig. 14 based on the considered data

```
Maximum, Minimum and Mean values for all the CSV files
Heart Rate (df1)
Max Heart Rate 2024-09-09: 232.0, Min Heart Rate 2024-09-09: 42.0, Mean Heart
Rate 024-09-09: 90.37208218293951
...
Breath Frequency (df2)
Max Breath Frequency 2024-09-09: 50.0, Min Breath Frequency 2024-09-09: 0.0,
Mean Breath Frequency 024-09-09: 21.58772136953955
...
Insulina Erogata (df5)
Max Insulina erogata 2024-09-09: 9.02, Min Insulina erogata 2024-09-09: 0.0,
Mean Insulina erogata 024-09-09: 2.476
...
Glicemia (df4)
Max Glicemia 2024-09-09: 261, Min Glicemia 2024-09-09: 1, Mean Glicemia
024-09-09: 148.51401869158877
...
Movement Index (df6)
Max MovementIndex 2024-09-09: 1.05, Min MovementIndex 2024-09-09: 0.017, Mean
MovementIndex 024-09-09: 0.21392105263157898
...
Stress Index (df7)
Max StressIndex 2024-09-09: 235.08, Min StressIndex 2024-09-09: 36.6, Mean
StressIndex 024-09-09: 91.22842105263159
...
Hrv Score (df8)
Max HrvScore 2024-09-09: 82.0, Min HrvScore 2024-09-09: 47.0, Mean HrvScore
024-09-09: 58.68421052631579
...
Insulina Basale (df9)
Max Insulina_basale 2024-09-09: 3.492, Min Insulina_basale 2024-09-09: 0.0, Mean
Insulina_basale 024-09-09: 1.5900000000000003
...
```

Figure 13: Examples of notebook summaries.

with the answers taken as ground truth.

With the help of the LangChain framework and Python libraries for extracting the knowledge based from our documents, we created a ChromaDB vector database to generate a retriever (using the

"as_retriever" method of the ChromaDB vd package) to generate contexts associated to the questions in our test list.

The context associated to a given question can then be used to specialize the answer submitted to a given LLM/SLM. Finally, we combined both the resulting retriever with a compressor to re-rank documents based on their relevance to a given query. The purpose of this combined structure is to streamline the retrieval and ranking process. This two-step process improves the quality of the final results, ensuring that the documents returned are not only relevant but also ranked according to their true relevance to the user's query.

We then perform a series of tests with different SLM models (and different sizes/number of parameters) considering an embedding fine-tuned on medical data (more precisely MedEmbed-small-v0.1). For the

Question	ground_truths
What was the maximum heart rate on 2024-09-09?	232.0
What was the minimum breath frequency on 2024-09-13?	9.0
What was the mean glucose level on 2024-09-11?	119.43
On which date was the maximum insulin administered, and how much was it?	2024-09-12, 9.76
What was the mean stress index on 2024-09-10?	50.36
What was the maximum heart rate on 2024-09-13?	156.0
What was the maximum HRV score recorded on 2024-09-11?	100.0
On which date was the maximum insulin basal level recorded, and what was its value?	2024-09-10, 4.387

Figure 14: Questions and ground truth.

considered list of questions the context retrieved by our retriever pipeline from the vector database turned out to contain the relevant part with respect to the question. Concerning hallucinations, the best results have been obtained with the Phi-3.5-mini-instruct model (0.25% wrong answers). These results are very preliminary since our dataset is still under construction and we are currently collecting additional data to perform more extensive training sessions and to create pipelines for redirecting queries to custom AI agents depending on the form of considered questions (e.g. descriptive question, query on tabular data, etc). As stated in the previous section, the LLM component should be seen as a conceptual demonstration rather than a final solution. A RAG system tailored specifically for biometric data analysis could be expected to provide more accurate and reliable responses.

7. Future Directions and Conclusion

This study demonstrates the feasibility of integrating wearable sensor data with AI-assisted analysis to support pediatric diabetes management. Our framework, which combines traditional data processing with machine learning techniques within a Jupyter-based environment, offers valuable insights into the interplay between physiological signals and glycemic trends. While the current implementation focuses on a single-patient case study, the architecture is designed to scale across larger cohorts and additional device types.

A key challenge remains in bridging structured data analysis with natural language interpretation. Although our JupyterHub environment efficiently handles pre-processing and visualization, translating these findings into actionable recommendations through AI-powered conversational agents is still in early development. Future work will focus on the integration of small language models (SLMs) trained on domain-specific data to facilitate interactive querying and personalized decision support. Furthermore, the integration of the Jupyter ecosystem with data centric architectures such as Spark, Streaming Spark or Dask and data acquisition engine such as Kafka and RabbitMQ are currently under consideration to support large scale processing in real time.

We also plan to evaluate the scalability, usability, and clinical value of the platform in a broader study, incorporating feedback from diabetologists and healthcare providers. Additionally, integrating more

advanced time-series modeling techniques and privacy-preserving machine learning approaches will be explored.

In conclusion, this work presents a novel methodology for leveraging wearable technology and AI to enhance pediatric diabetes care. The findings underscore the importance of multi-modal data integration and local computation for privacy and clinical utility. With further refinement, this system has the potential to evolve into a robust clinical decision support tool that empowers both healthcare professionals and patients.

Ultimately, integrating such platforms into hospital IT infrastructures and electronic health record systems could bring AI-driven, personalized treatment planning into routine clinical workflows, supporting more adaptive and responsive care for young patients with diabetes.

Declaration on Generative AI

The paper has been written by the authors. Generative AI has been used for language corrections (DeepL) and to support code generation using Copilot.

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