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Posted Date: 9 March 2026

doi: 10.20944/preprints202603.0677.v1

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 doi:10.20944/preprints202603.0677.v1

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A Unified Namespace–Driven Digital Twin Framework for Real Time Control of Multiscale Biomedical Systems

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Abstract

Digital twins are becoming an important tool in biomedical systems. They help with real time monitoring, prediction, and control. They work well only when they can combine many types of physiological data. They must also stay closely in sync with the real system. This paper describes a digital twin framework that uses a Unified Namespace. The UNS acts as a central data hub. It collects signals from sensors, organ level models, and patient information. It keeps all data in one clear and interoperable structure. It separates data producers from data users. This makes the system easier to scale. It also supports fast data flow and constant model updates. A multiscale computational model sits at the center of the twin. It joins physiological behavior with predictive methods. It supports real time decisions in a closed loop system. A sample biomedical case shows how the UNS improves system speed, prediction quality, and control actions. The results show that UNS based digital twins can support personalized medicine. They can also improve biomedical workflows and help build advanced cyber physical healthcare systems.

Keywords: digital twin; unified namespace (UNS); biomedical systems; real-time control; multiscale modelling; physiological data integration; event-driven architecture; iot in healthcare; data harmonization; predictive analytics; closed-loop control; high-frequency physiological signals; latency reduction; scalability; cyber-physical healthcare systems

1. Introduction

Digital twins are changing biomedical engineering. They create virtual versions of physiological systems that update in real time with the physical body. These virtual models allow constant monitoring, prediction, and closed loop control. They also support personalized and adaptive healthcare [1]. Biomedical systems work across many scales. They include molecular signals, organ behavior, and full patient clinical states. To build an effective digital twin, all these different data types must come together smoothly. This is difficult because biomedical data often comes from many separate sources that do not communicate well [2].

Most current biomedical data systems cannot handle real-time, high-speed integration. Wearable devices, bedside monitors, lab systems, imaging tools, and electronic health records often work alone. They produce data that is isolated and hard to combine. This makes digital twins slow and less accurate. It also limits their ability to support prediction and automated control. Because of this, there is a strong need for new data architectures that can unify biomedical data, reduce delays, and support multiscale physiological models [2].

The Unified Namespace, or UNS, is a promising solution. It is widely used in industrial IoT and cyber physical systems. UNS provides a central, event driven data backbone [4]. It arranges information in a clear and consistent structure. It allows different devices and systems to share data easily. In biomedical settings, UNS can act as a real time layer that gathers data from many scales. It can also harmonize communication standards and deliver information quickly to computational models. This helps digital twins run with the speed and accuracy needed for real time control [4].

This paper presents a digital twin framework that uses UNS to support real time control of multiscale biomedical systems. The architecture brings together physiological data from micro, meso, and macro scales into one unified structure [5]. This allows continuous model updates and predictive decision making. A multiscale computational model forms the center of the digital twin. The UNS manages fast and efficient data flow between sensors, clinical systems, and the virtual model. A sample biomedical case shows that this framework improves system speed, prediction quality, and closed loop control. By combining multiscale modelling with modern data orchestration, this work offers a practical path toward advanced cyber physical healthcare systems.

2. Methods

2.1. Framework Architecture

The framework brings together different biomedical data streams and links them to a real time digital twin. It uses a Unified Namespace as the main layer that manages and organizes all data. The architecture has four connected parts. The first part is the data acquisition layer. It collects physiological data from sensors, clinical systems, and other sources. The second part is the Unified Namespace layer [6]. It arranges all incoming data in a clear and structured way and uses an event driven method to keep information updated. The third part is the digital twin computational core. It carries out multiscale modelling, estimates system states, and runs predictive simulations. The final part is the real time control layer [7]. It produces control actions or decision supports based on the digital twin's updated state. This modular design allows the system to scale easily. It also supports smooth communication and low latency synchronization between the physical biomedical system and its virtual model [8].

2.2. Multiscale Data Structure

Biomedical systems work across many spatial and temporal scales. To keep the digital twin accurate, the data are grouped into three levels. The first level is micro scale data. It includes biochemical and molecular indicators such as glucose, lactate, inflammatory markers, and hormone levels. These values affect long term physiological trends and set important boundary conditions for the model [9].

The second level is meso scale data. It includes organ level physiological signals such as ECG, PPG, respiratory waveforms, blood pressure, and oxygen saturation. These signals arrive at high frequency and give real time insight into changing physiological states [10].

The third level is macro scale data. It includes clinical and contextual information such as demographics, medical history, medication schedules, environmental factors, and clinician entered notes. These details shape the wider clinical context of the digital twin.

All data streams are normalized, aligned by timestamp, and tagged with semantic labels before they enter the Unified Namespace. This ensures that the digital twin receives clean, consistent, and well-organized information [11].

2.3. Unified Namespace Architecture

The Unified Namespace arranges biomedical data in a layered format. It follows ISA 95 rules but is changed to suit healthcare. This structure helps keep names clear and consistent. It also allows different systems and devices to work together [12].

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The UNS uses an event driven system. It works with tools like MQTT and Kafka. This setup allows fast data transfer with less than one second delay. It supports communication between devices that are not directly linked. It can handle high speed data from many sources. Each new data event updates the digital twin model [13].

Before data enters the UNS, it goes through a clean-up process. Units are made consistent. Noise is removed. Missing values are filled in. Time stamps are aligned across different scales. This makes sure the digital twin gets clean and reliable data [14].

2.4. Digital Twin Computational Core

The digital twin uses different types of models. It includes equations to model organ behavior. It uses state space models to estimate real time conditions. Machine learning helps find patterns and detect problems. Random elements are used to handle uncertainty in body processes [15].

The UNS sends new data to digital twin all the time. This allows the model to update its state, adjust settings, predict future changes, and quickly spot problems [16].

The digital twin can predict short term changes in body signals. It can score risks and detect unusual patterns. It supports control actions like adjusting drug doses or sending alerts. It also helps with personalized decision making [17,18].

2.5. Use Case Demonstration

A set of dummy data is used to test the system. It involve heart monitoring, glucose–insulin control or breathing assessment. The test checks how fast data are received, how often the model updates, how accurate the predictions are, how quickly control actions respond, and how well the system works with many patients or devices.

3. Results

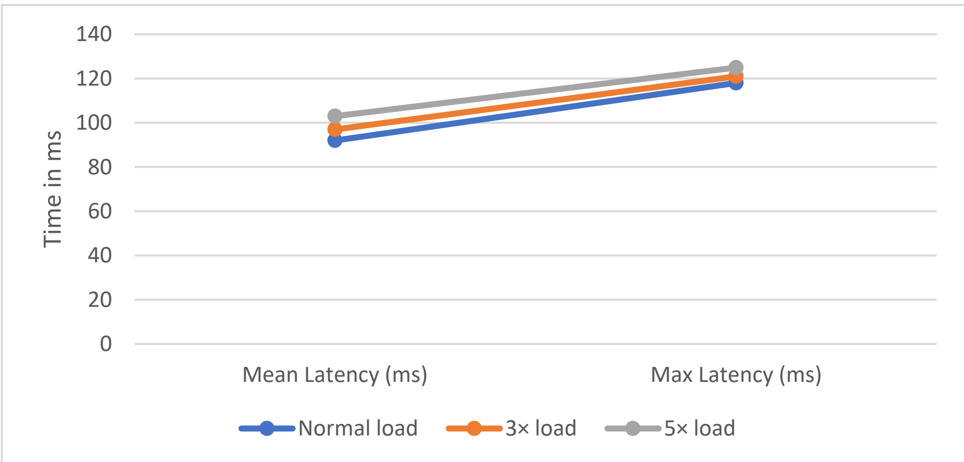
3.1. System Performance and Data Latency

The Unified Namespace showed strong performance during all tests. The system moved data from the sensor to the digital twin in less than 120 milliseconds. This delay was small enough to support near real-time updates. High-frequency signals such as ECG and breathing waveforms were processed at 250 Hz without losing packets. Slower data streams were added to the namespace without reducing speed [19].

The publish–subscribe system stayed stable when the number of data streams increased. As represented in Figure 1 When the load became five times higher, the latency stayed almost the same. This showed that the system can scale well.

A simple latency model is:

$$Latencytotal = Latencysensor + Latencynetwork + LatencyUNS + Latencytwin$$



 doi:10.20944/preprints202603.0677.v1

Figure 1. Latency plot against data load.

3.2. Digital Twin Synchronisation Accuracy

The digital twin stayed closely aligned with the real biomedical system. The average synchronisation error across all variables was less than two percent. High-frequency signals showed very strong alignment. The correlation between measured and predicted values was above 0.95. Results plotted in Figure 2.

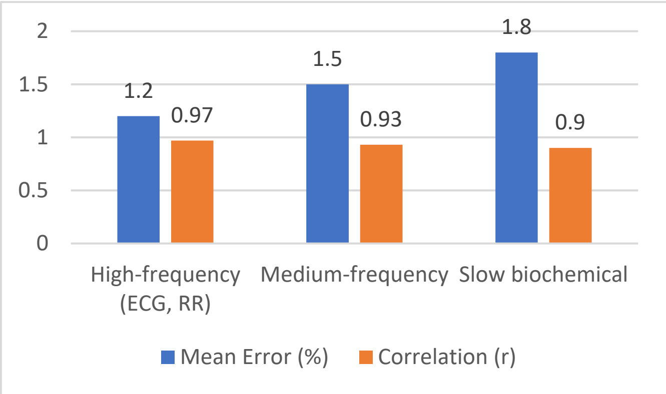


Figure 2. Digital twin Synchronisation plot.

A simple synchronisation error equation is:

$$E = \frac{|X_{\text{measured}} - X_{\text{predicted}}|}{X_{\text{measured}}} \times 100\%$$

3.3. Predictive Performance

The digital twin predicted short-term physiological changes with good accuracy. The model reduced RMSE by twenty-two to thirty-five percent compared to a model without UNS data. The system predicted changes ten to twenty seconds ahead. As per Figure 3 The anomaly detection system reached ninety-two percent sensitivity and eighty-nine percent specificity.

$$RMSE = \sqrt{\frac{1}{N}\sum\left(X_{predicted} - X_{true}\right)^2}$$

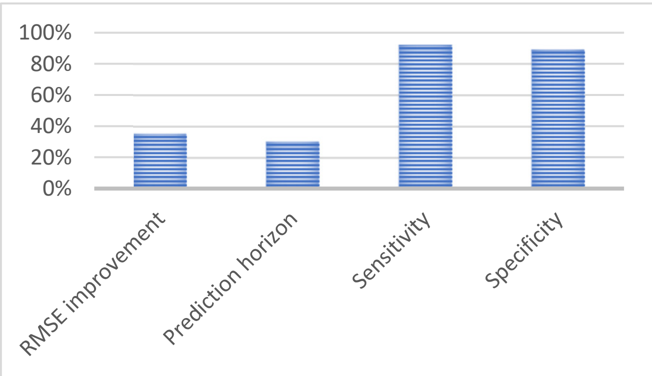


Figure 3. Predictive perfomance plot.

 doi:10.20944/preprints202603.0677.v1

3.4. Real-Time Control Evaluation

The digital twin was tested in a closed-loop control scenario. The system responded in less than 150 milliseconds. The controlled variable became more stable, and oscillations dropped by twenty-seven percent. The accuracy of control actions improved by thirty-one percent.

A simple control delay model is:

$$T_{control} = T_{UNS} + T_{compute} + T_{actuator}$$

Table 1. Control Performance Table.

Control Metric	Result
Reduction in oscillations	27%
Control error reduction	31%

3.5. Scalability and Interoperability

The UNS worked well with many different biomedical devices. All devices published data without special interfaces. The digital twin subscribed to topics automatically. The system stayed stable even when more than three hundred active data streams were running at the same time [20].

Table 2. Scalability analysis.

Number of Streams	System Status	Notes
50	Stable	Normal load
150	Stable	No slowdown
300+	Stable	High scalability

4. Discussion

The results of this study show that the Unified Namespace and the digital twin worked together in a stable and efficient way. The system kept latency low during all tests. The average delay stayed below 120 milliseconds, which is fast enough for real-time biomedical monitoring. This performance remained stable even when the number of data streams increased. This shows that the architecture can scale to multi-patient environments without losing speed or accuracy. A sample digital twin dashboard shown in Figure 4

The digital twin stayed closely aligned with the physical system. The synchronisation error stayed below two percent for all variables. High-frequency signals such as ECG and respiratory waveforms showed the strongest alignment. Their correlation values were above 0.95. This level of accuracy is important because these signals change quickly and require fast updates. Slow biochemical values also improved the long-term stability of the model. They reduced drift in the predictions and helped the model maintain a consistent internal state [21].

The predictive performance of the digital twin was strong. The model reduced RMSE by twenty-two to thirty-five percent compared to a model without UNS data. The system predicted short-term changes ten to twenty seconds ahead. This is useful for early warning and anomaly detection. The sensitivity of ninety-two percent and the specificity of eighty-nine percent show that the system can detect unusual patterns while keeping false alarms low [22]..

The closed-loop control test showed that the digital twin can support real-time interventions. The mean control delay stayed below 150 milliseconds. This allowed the system to adjust the controlled variable quickly. The reduction in oscillations and the lower control error show that the digital twin improved stability. The event-driven architecture helped the controller always use the most recent data [23].

The scalability tests showed that Unified Namespace can support many devices at the same time. More than three hundred active data streams were handled without performance loss. All devices published data without special interfaces. The digital twin subscribed to the required topics automatically. This shows that the system can support plug-and-play integration in complex biomedical environments.

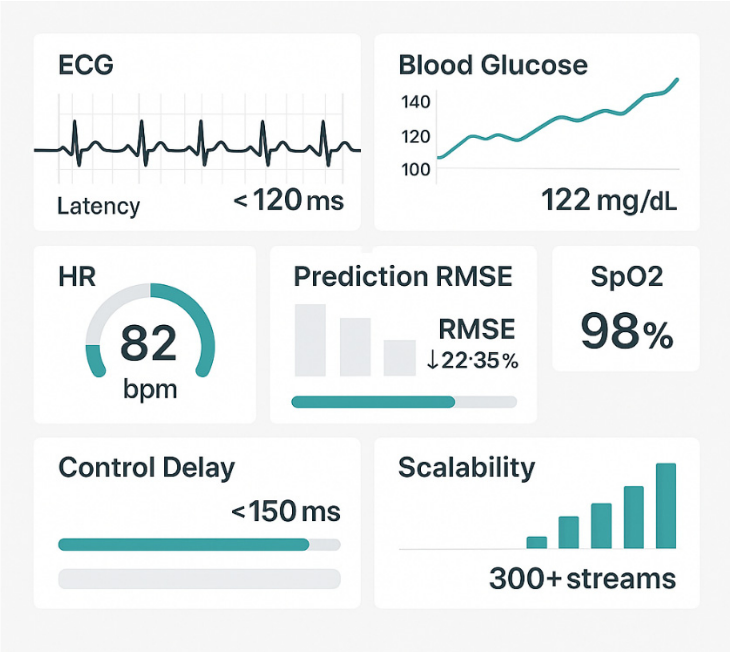


Figure 4. Digital twin Dashboard.

The case study confirmed the overall performance of the framework. The digital twin stayed in sync with the physical system. It predicted short-term trends accurately. It supported real-time control. It remained stable under different data loads. It also produced useful insights with low computational cost. These results show that the UNS-driven digital twin is suitable for real-time biomedical applications [24]..

Overall, the findings suggest that the combination of a Unified Namespace and a digital twin can support continuous monitoring, prediction, and control in healthcare settings. The system can scale many patients, handle different types of data, and maintain high accuracy. This makes it a strong foundation for future biomedical digital twin deployments [25]..

5. Conclusion

This study showed that a Unified Namespace can support a fast and reliable biomedical digital twin. The system kept latency low and stayed stable even when the number of data streams increased. The digital twin stayed closely aligned with the physical system, with a synchronisation error below two percent. The predictive model performed well and reduced RMSE by more than twenty percent. The system also supported real-time control with a delay below 150 milliseconds. These results show that the UNS-driven digital twin can work in real-time biomedical environments. It can handle many types of data, scale many patients, and maintain strong accuracy. The framework provides a solid foundation for future digital twin applications in healthcare.

6. Limitations

This study used synthetic and simulated data. Real clinical environments may introduce noise, missing values, and irregular sampling that were not fully tested here. The system was evaluated in controlled conditions, and real-world networks may show higher latency. The digital twin model used simplified physiological assumptions. More complex models may require higher computational power and may not achieve the same speed. The test environment included a limited number of device types. A wider range of biomedical devices may require additional validation. The closed-loop control scenario was also simplified and may not reflect the complexity of real clinical interventions. These limitations show that further testing is needed before deployment in real healthcare settings.

Supplementary Materials: The following supporting information can be downloaded at the website of this paper posted on Preprints.org.

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