Smart Mechatronic Assistive Systems for Inclusive Education: Integrating Mechanical and Electrical Engineering Innovations to Support Learners with Special Needs

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ABSTRACT:

Climate change and environmental pollution have led to the increased need for developing sustainable economic and environmental models that could be capable of considering the intricate relationships between economics, energy, industries, and carbon dioxide emissions. This study developed and evaluated machine learning and big-data frameworks for greenhouse gas emission prediction and sustainability-oriented decision support. A quantitative predictive approach was applied using a multi-regional and multi-sector dataset containing 179,185 observations from 1995 to 2022. Greenhouse gas emissions were modeled using Value Added, Employment, Energy Carrier Net Total, Region, Sector, and Year. Linear Regression, Random Forest, and XGBoost were implemented and evaluated using Mean Absolute Error, Root Mean Square Error, and the coefficient of determination (R^2). Feature importance and SHAP analysis were additionally performed to improve model interpretability and transparency. The results demonstrated that XGBoost achieved the highest predictive performance, with MAE = 0.6007, RMSE = 0.9172, and R^2 = 0.9179, outperforming both Random Forest and Linear Regression. Energy consumption emerged as the strongest determinant of greenhouse gas emissions, while electricity production, waste management, petroleum refining, and livestock-related sectors significantly contributed to emission variation. The results show that the machine learning ensembles deliver accurate and understandable systems that can be used for environmental-economics prediction and sustainable decision making. This proposed system may aid in carbon-based planning,

sectoral sustainability evaluation, and environmental policy formation.

Keywords: Integrating Mechanical; Electrical Engineering; Smart Mechatronic.

1. Introduction

Inclusive education is increasingly gaining importance in today's educational systems because learners with disabilities and those with special educational needs need an environment where access to learning is equal, they are provided with appropriate support, and they can take an active part. This agenda has been reinforced by the evolution of assistive technology that has allowed students with sensory, physical, cognitive, communication, and learning impairments to better interact with instructional materials, assistive devices, and classmate learning. Assistive technologies can enhance accessibility, autonomy, participation, and academic inclusion when choosing the right AT to suit the needs of the learner and ensure its use in the learning context and with proper pedagogical planning (Fernández-Batanero et al., 2022). This provides a solid foundation for developing innovations that are grounded in the engineering design process rather than merely adapting an existing classroom to accommodate learners and that involve sensing, interpreting, and supporting learners' states in real-time.

The integration of digital platforms, adaptable interfaces, artificial intelligence, connected devices, and data-based aids has created a new level of inclusive education, smart learning environments. When the design of technological learning environments is based on accessibility and inclusive pedagogy, it can facilitate personalized access to instruction, decrease barriers to participation, and enhance engagement for students with disabilities (Dhouib et al., 2025). However, the successful implementation of these technologies requires teacher preparedness, institutional support, usability, and affordability, in addition to the infrastructure. The barriers to implementation are still very high, particularly if technology is implemented without adequate training, maintenance planning, and responding to the individual needs of learners in relation to their accessibility needs (Murillo-Jiménez et al., 2025).

Technology inclusion encompasses a variety of systems, such as communication, sensory, adaptive software, mobility-support systems, learning platforms, robotics, and intelligent monitoring. Recent research indicates that inclusive education technologies range widely in their purpose, function, and design, thus reinforcing the importance of multi-disciplinary approaches involving both pedagogical, mechanical, electrical, and computational skills (Navas-Bonilla et al., 2025). Assistive technology has also been linked to increased engagement, communication, and participation for learners with disabilities, but matching the AT capabilities, learner needs, and context of learning is important to the effectiveness of AT for learning (Abdelwahab et al., 2025).

The transition from traditional assistive devices to intelligent and immersive technology has opened up opportunities for pupils with specific learning difficulties and other needs. New systems are also starting to come out, such as virtual environments, wearable technologies, adaptive interfaces, and metaverse tools that can enhance accessibility in higher education and specialized learning settings (Yenduri et al., 2023). Innovative learning environments are not just about devices: they require inclusive design models, which consider both physical space and social participation, teaching practice, and learner agency (Page et al., 2023). For smart mechatronic systems, where the support of the learner might need both mechanical, electronic, and computational responses, these kinds of models are even more relevant.

The use of AI in special education has also grown in significance, such as in personalized learning, support systems for assessments, behavior monitoring, communication tools, and adaptive

feedback. While AI-powered tools can assist in understanding learner needs and offering personalized support, their application should adhere to ethical standards, transparency, and human supervision, so as not to deceive or mislead learners (Hussein et al., 2025). Other types of assistive technologies, such as augmentative and alternative communication systems (AAC), also illustrate how technology can be used to facilitate language development and participation of students with specific learning disorders (Dumitru, 2025). The developments hint that the need for inclusive education is for technologies that can meet the academic tasks, but also the different communication, sensory, motor, and physiological needs.

Another key focus of inclusive classroom innovation is robotics. Social interaction, engagement, communication, and structured learning tasks can be aided by the implementation of robots in pedagogical design that is inclusive (Diaz-Boladeras et al., 2025). The topic of social robots has been explored extensively in special education, especially when it comes to persons for whom structured, predictable, and interactive support systems are beneficial (Papakostas et al., 2021). Results of research with children and young people with autism suggest that robotic systems can contribute to social, communicative, and behavioral outcomes, but the results depend on the type of intervention, the characteristics of the child or young person with autism involved in the interaction, and the context in which the systems are implemented (Kouroupa et al., 2022).

Smart mechatronic assistive systems are an amalgamation of these developments. These systems can incorporate mechanical structures, sensors, actuators, embedded electronics, biosignals acquisition, control logic, and adaptive feedback into a learner-support technology. This method can be used in inclusive education environments to monitor posture, assist with mobility, detect exhaustion, regulate sensory input, provide haptic feedback, adjust seating positions, adjust the environment, and alert teachers. The mechanical movement can be obtained from wearable accelerometers, and the electrical biosignals, such as heart rate, skin conductance, pulse activity, temperature, and workload-related variation, can be obtained from the wearable physiological sensors. These data streams can be utilized for generating learner state proxies, which will be useful in providing timely assistive responses.

In the present study, the feasibility of multiple modal (wearable-sensor) data used to support the design of a smart mechatronic assistive system for inclusive education is studied. The study applied the combination of accelerometer and physiological data as proxy engineering inputs for the monitoring of movement, interpretation of biosignals, and mapping of assistive response. The aim was not to prove the effectiveness of an intervention in class or determine the needs of learners with special needs, but to design and test a technical support system to link mechanical and electrical innovations to the support functions of learners with special needs.

Objectives of the study:

1. To evaluate the feasibility of multimodal wearable-sensor data for smart mechatronic assistive-system design.
2. To analyze accelerometer and physiological signals as mechanical and electrical inputs for learner-state monitoring.
3. To map sensor-derived movement and biosignal features to inclusive education support functions for learners with special needs.

2. Methods

2.1 Study Design

This research employed the design of secondary data analysis and the development of an engineering framework. The goal was to assess the potential of multimodal data obtained from wearable sensors to aid in the design of a smart mechatronic system for inclusive education. No direct testing of a specific intervention in the classroom has been done in the dataset; it has been used to model the sensing, signal processing, and decision support layers of an assistive system for learners with special needs.

2.2 Dataset Source and Description

The multimodal data from the MET wearable-sensor dataset were used in the study, which comprised a multimodal set of recordings from seven participants (Bermudez-Edo et al., 2025). The data consisted of files for accelerometer, blood volume pulse, electrodermal activity, HR, inter-beat interval, temperature, activity-tag, and age. Accelerometer data were used as a representation of the mechanical-motion component, and physiological signals were used as a representation of the electrical biosensing component.

This set of data was used as a proxy engineering set since it was not gathered specifically from special needs learners or classroom settings.

2.3 Mechatronic Assistive-System Framework

A master plan involving four layers was created. The sensing layer featured movement monitoring and physiological biosensing by the use of an accelerometer. The signal-processing layer included the processing of the sensor signals, such as cleaning, organizing, segmenting, and transforming the sensor signals into features.

The decision-support layer used movement and physiological data as proxies of the learner-state. Assistive-response layer was mapped out for different states detected to potential education supports such as posture prompts, mobility alerts, sensory-regulation cues, break recommendations, adaptive seating responses, and teacher notifications.

2.4 Data Preprocessing

The participants' folders and the sensor modalities were used to open and view the ZIP archive. Readability of the files, completeness, and structure were checked. For each participant and file type, sensor streams were set up. The data from the accelerometer was used as the three-axis motion data, and the data from the heart rate, BVP, EDA, IBI, and temperature sensors were used as biosignal data streams. Activity-tag files were conservatively looked at, as the archive did not offer a thorough label dictionary.

2.5 Feature Extraction and Analysis

The features extracted from the accelerometer data were movement-related features, which were extracted through data processing with Python, such as mean acceleration, standard deviation, root mean square acceleration, vector magnitude, and movement intensity. Physiological features were also extracted in Python and were added, such as mean heart rate, inter-beat interval variation, electrodermal activity level and variability, blood volume pulse variation, and temperature trends.

Descriptive sensor profiling, broad movement-state characterization, and sensor output mapping to help mapping to assistive education functions were the focus of the analysis. All classification tasks were more a proof-of-concept analysis than a prediction of the status of disability or learning performance.

3. Results

3.1 Dataset Structure and Sensor Availability

MET data consisted of 7 participant folders, 4 of which were male-coded, and 3 that were female-coded. The age of the participants ranged from 16 to 54 years. Files in each folder contained accelerometer, blood volume pulse, electrodermal activity, heart-rate, inter-beat interval, temperature, activity-tag, and age files. There were no missing core sensor files.

The total signal rows recorded were 2,035,904, which was sufficient for a complete and suitable multimodal engineering analysis. The inventory of data sets and the availability of sensors on the individual participants are presented in Table 1.

Table 1. Dataset inventory and sensor availability

Participant	Age	ACC	BVP	EDA	HR	IBI	TEMP
F-01	54	80,862	161,667	10,110	2,517	600	10,120
F-02	16	82,374	164,692	10,278	2,564	720	10,288
F-03	54	110,118	220,231	13,740	3,432	1,470	13,744
M-01	17	81,372	162,723	10,158	2,533	480	10,176
M-02	54	81,924	163,834	10,224	2,550	570	10,232
M-03	16	81,240	162,404	10,140	2,528	990	10,160
M-04	54	100,812	201,652	12,606	3,141	1,320	12,608
Total	—	**618,702**	**1,237,203**	**77,256**	**19,265**	**6,150**	**77,328**

3.2 Sensor Composition and Engineering Role

Mechanical-motion and electrical-physiological signals were included in the data set. The mechanical sensing component was represented by accelerometer data, and the electrical biosensing components were BVP, EDA, HR, IBI, and TEMP. The average length of recording time per participant was about 46 minutes, sufficient for the modelling of assistive systems in short sessions. Table 2 lists the sensor modalities and their engineering functions.

Table 2. Sensor modalities and the engineering role

Sensor	Total rows	Sampling structure	Engineering role
ACC	618,702	32 Hz	Movement, posture, and activity monitoring
BVP	1,237,203	64 Hz	Cardiovascular waveform monitoring
EDA	77,256	4 Hz	Skin-conductance and arousal monitoring
HR	19,265	1 Hz	Heart-rate and physical-load monitoring
IBI	6,150	Event-based	Beat-to-beat interval variability proxy
TEMP	77,328	4 Hz	Temperature and comfort monitoring

3.3 Activity-Label Processing

The labels for activities were conservatively reviewed, as the data does not contain a full dictionary of label names. Labels that were retained were classified as low-mobility, active-task, walking-related, and stair transition states. This allowed for the wide activity-state characterization without clinical and/or educational inferences. Retained activity labels and functional interpretations are given in Table 3.

Table 3. Retained activity labels

Label	Segments	Total duration	Interpretation
lie	7	29.24 min	Low-mobility state
r	7	28.58 min	Resting state
d	7	29.73 min	Desk-task state
wd	7	25.41 min	Active task
wp	7	26.08 min	Active task
ws	7	23.05 min	Walking-related state
wr	7	21.81 min	Walking-related state
wf	7	22.69 min	Highly active movement
ds	8	3.78 min	Downstairs transition
us	8	3.95 min	Upstairs transition

3.4 Mechanical Movement Findings

The mechanical sensing component was evaluated using both the amplitude and intensity of movement as determined by the accelerometer. There was low mobility intensity for low mobility labels, mid mobility intensity for active labels, and high intensity for stair transition labels. This suggested that the feature of the accelerometers could be used to assist with the detection of wide movement states in a mechatronic assistive system. Table 4 presents the movement profiles as measured using the accelerometer, based on activity state. A plot of the intensity of movement based on the accelerometer data is shown in Figure 1 for each activity state.

Table 4. Accelerometer-derived movement profile

Label	State	Mean vector magnitude	Movement intensity
lie	Low mobility	63.32	1.00
r	Low mobility	64.04	1.10
d	Desk task	63.43	1.76
wd	Active task	65.07	9.09
ws	Active movement	66.10	10.35
wp	Active task	66.74	14.83
us	Stair transition	68.76	16.72
wr	Active movement	69.04	16.91
wf	Highly active movement	74.32	24.07
ds	Stair transition	67.70	25.33

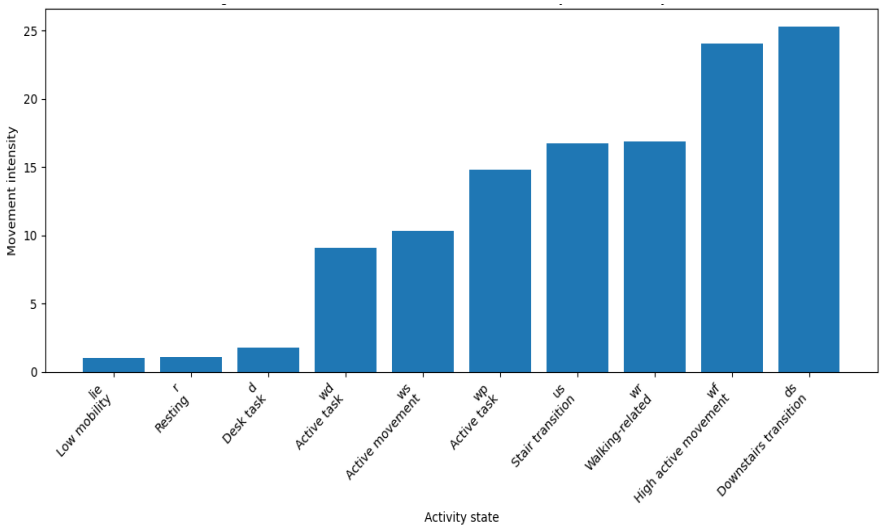

Figure 1. Accelerometer-Derived Movement Intensity Across Activity States

A proof-of-concept grouping was used to separate active and low-mobility states (w, d corresponds to low-mobility states, and wd, wp, ws, wr, wf, ds, us are for active states). Complete separation with 100% accuracy, precision, recall, and F1-score was achieved with movement intensity. This was only seen as technically possible as they weren't predicting disability status, learning performance, or educational need.

3.5 Electrical Biosignal Findings

The mechanical movement data were supported by electrical biosignals. There was also a higher mean heart rate for active states and a lower mean inter-beat interval for active states than for low-mobility states, indicating increased physical load. The variance of EDA was not as consistent, and the data were seen as a secondary signal of arousal. The temperature was relatively stable and more conducive to comfort or Environmental Monitoring. The differences in physiological signals across broad activity states are presented in Table 5. The means of the physiological signals across the two states of activity and low mobility are compared in Figure 2.

Table 5. Physiological signals by broad activity state

Activity state	Segments	Mean HR	Mean EDA	Mean TEMP	Mean IBI
Active movement/task	51	93.64	1.12	32.96	0.82
Low mobility	21	68.97	1.21	33.68	0.90

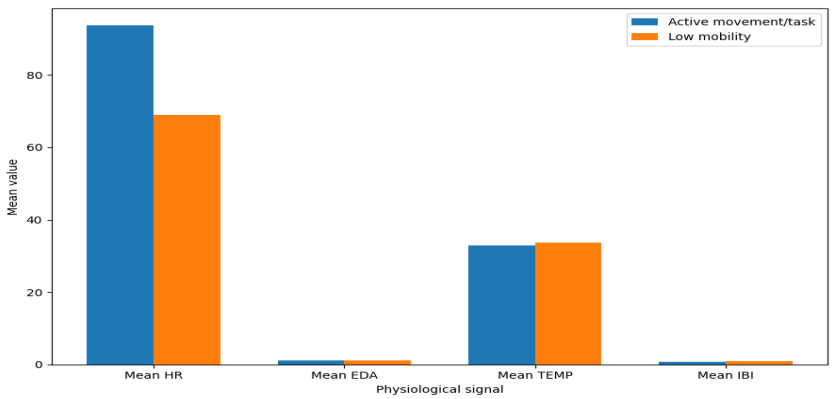

Figure 2. Physiological Signal Comparison by Broad Activity State

3.6 Assistive-System Feasibility

The overall results confirmed the possibility of implementing a sensor-fusion approach for smart mechatronic assistive systems. Acceleration signals assisted movement monitoring, posture, and mobility transition monitoring. The monitoring was supported by physiological signals that included physical-load, arousal-related, and comfort-related monitoring. The outputs can be directed to an assistive response like posture prompts, mobility alert, sensory-regulation cue, rest recommendation, adaptive seating response, and teacher notification. The data helped in the engineering feasibility and system design. It does not directly measure inclusive classroom outcomes or outcomes of learners with special needs due to the fact that it was not collected in this population or setting. Figure 3 shows the correlations between movement and physiological characteristics.

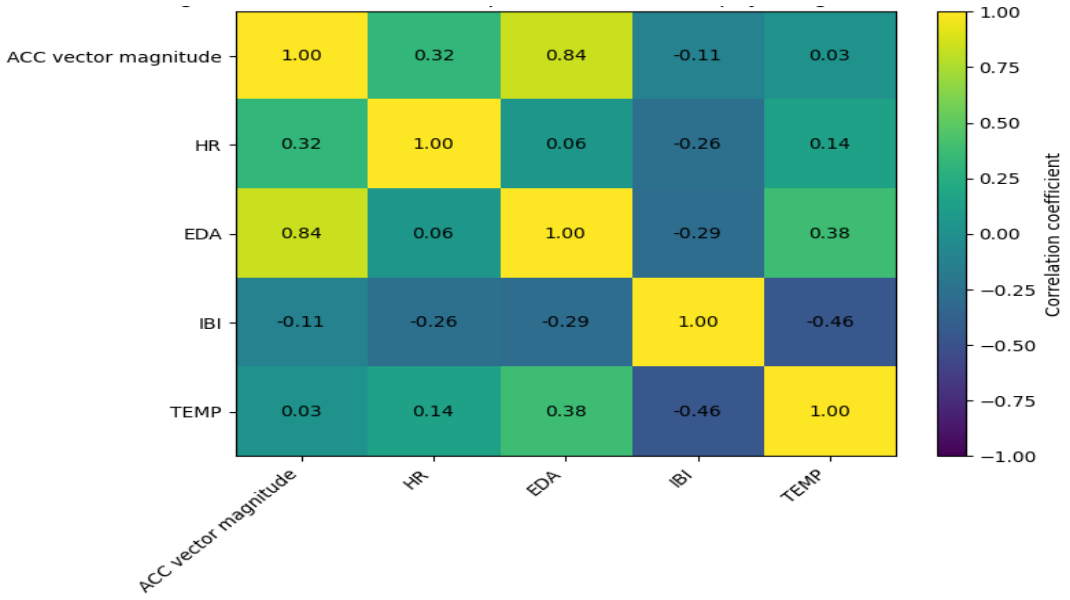

Figure 3. Correlation Heatmap of Movement and Physiological Features

4. Discussion

In the present study, the feasibility of the use of multimodal data acquired using wearable sensors to aid in the design of an assistive system for inclusive education with the use of smart mechatronics has been investigated. The results revealed that the accelerometer-based intensity of movement was clearly different between the low-mobility state and the active-movement state and active-movement-stair transition state. This enabled the mechanical sensing part of the proposed framework, where movement of the body, variability related to posture, and mobility transitions can be tracked from inertial data worn by the user. The research on human activity recognition has consistently demonstrated that inertial and physiological sensors are able to provide useful information regarding the human activity, state of activity, and context-aware monitoring, and it can be used in the design of assistive systems (Demrozi et al., 2020).

Accelerometer data were especially applicable to the mechatronic aspect of the study. The low-mobility states (lying, resting, and desk-related) also had low values for the movement intensity, which were significantly higher for the walking-related and stair-transition states. This difference revealed that mechanical motion capabilities could be utilized in a smart classroom support system to identify prolonged inactivity, high motion variation, a switch from seated to mobile, and/or a motion pattern that might need support. Wearable-sensor studies have demonstrated the potential for activity recognition models to learn from the constrained data into which the sensor stream is recorded, particularly when the features can be extracted from the data according to a structured approach or using learning algorithms

(Ni et al., 2020). These patterns can be applied in an inclusive education setting for adaptive seating, posture prompts, mobility alerts, or notifications for teachers.

Physiological findings added to the framework and extended beyond mechanical movement monitoring. There was a higher mean HR and lower mean inter-beat interval (IBI) for active movement and task states compared with low-mobility states, suggesting that the physical load was higher when active. EDA and temperature did not provide as direct a separation between broad activity states as did the others, but provided additional information on autonomic variation and physiological comfort. The multimodal fusion has been explored recently, demonstrating that the fusion of three signals: PPG, EDA, and Accel could be useful for HAR, because each of them captures a different aspect of the human body state (Gilmore & Nasseri, 2024). This reinforces the idea that mechanical and electrical signals should not be considered separately, but rather in conjunction with other signals that are used for sensor fusion-based assistive systems.

It was also concluded that when interpreted with careful consideration, the physiological biosignals could be a part of learner-state proxy monitoring. Heart rate, inter-beat interval, electrodermal activity, and temperature are indirect measures of physical exertion, arousal, and comfort, and not measures of stress, disability, or learning difficulty in and of themselves. Research on real-time stress prediction with wearable sensors has highlighted the potential of physiological data for effective state prediction in time, but the performance of the model depends on its contextual calibration, the quality of the physiological signals, and the individual variability (Lazarou & Exarchos, 2024). Based on this, within the proposed assistive framework, it would be best to use physiological values as support triggers or dashboard indicators, not a diagnosis.

The study also coincided with the growing advancements in Wearable Sensing and Personalized Monitoring. Physiological and behavioral data are gathered from wearable devices for continuous monitoring, allowing for personalized support and monitoring in health and human-performance applications (Babu et al., 2024). The same rationale could be used with students who get tired, have mobility challenges, sensory sensitivities, and/or trouble holding their bodies in a comfortable learning posture in inclusive classrooms. A mechatronic system could be developed to combine various types of wearable sensing with actuators, haptic feedback, adaptive seating, and/or environmental controls to provide nonintrusive support during learning activities.

Monitoring stress and discomfort is a very relevant, but sensitive application. Many studies have focused on the use of wearable pain and stress sensors for the detection of pain and stress (Chen et al., 2021), but the physiological responses must be carefully interpreted, as physical activity, emotion, environment, and individual differences affect the response. This restriction was also confirmed in the current study, since the electrodermal activity did not have a simple state-based pattern. For this reason, the proposed system should not rely on automatic classification of a student's distress or disengagement, but rather on signals from the physiological processes that are probabilistic and must be interpreted by the teacher.

The relevance of this framework for inclusive education is greatest for those learners who might benefit from movement-aware, arousal-aware, and/or comfort-aware support. Physiological monitoring (including wearable devices) has been explored with individuals with autism spectrum disorder (ASD), as well as for monitoring stress and supporting self-regulation of others, suggesting a potential for learners who experience sensory regulation or emotional regulation issues (Cano et al., 2024). Wearable technologies have also been proposed to support people with ASD, although there is limited evidence to rely on that is based on usability, personalization, acceptance, and ethical implementation (Hernández-Capistrán et al., 2024). The results stress the importance of the development of assistive systems that are

adaptive, non-stigmatizing, and privacy-preserving.

The main drawback of the study was that the data were not gathered from learners with special needs or even an inclusive classroom setting. The results were therefore engineering (and not educational) feasible. The data was used to enable the technical design of a smart mechatronic assistive framework, demonstrating the possibility of extracting, comparing, and mapping mechanical features with electrical biosignals to facilitate functions. The framework should be further validated in educational contexts, with individuals with diverse accessibility requirements, and be evaluated for usability, acceptability, safety, educational outcomes, and privacy. Overall, the results confirmed the possibility of the integration of mechanical and electric engineering innovations into sensor-driven assistive systems for inclusive education.

5. Conclusion

The technical feasibility of smart mechatronic assistive systems for inclusive education was shown by the use of multimodal data from wearable sensors. Accelerometer-derived movement shows distinct states of low mobility, desk task, active movement, and stair transition, which provides evidence of the role of mechanical sensing in posture, mobility, and activity monitoring. Electrical biosensing signals, such as heart rate, inter-beat interval, electrodermal activity, blood volume pulse, and temperature, were used as complementary input parameters from the physiological signals for estimating physical load, autonomic variation, and comfort-related changes. These signals could be combined in an integrated system that would enable sensor fusion for mapping mechanical and electrical engineering innovations to supportive responses, including posture cues, mobility cues, adaptive seating, sensory-regulation cues, rest cues, and teacher-focused cues. The data were not directly about learners with special needs or classroom-level outcomes, so findings should be considered as evidence of engineering feasibility and not evidence of educational effectiveness. This is an ideal framework to be tested in inclusive classrooms with a group of learners with varying levels of support needs, with consideration of usability, privacy, accessibility, consent, and ethical implementation in the future.

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