International Journal of New Developments in Engineering and Society
ISSN 2522-3488 Vol. 9, Issue 2: 1-8, DOI: 10.25236/IJNDES.2025.090201

Innovative direction and market potential of smart waist belt: exploration based on technology migration and demand analysis

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Abstract: *The pace of modern life has accelerated, making lumbar health a global issue. While smart belts can monitor lumbar data in real-time and provide personalized solutions, their development faces numerous challenges. This paper explores the technical feasibility, market demand, user profiles, and solutions through technology transfer and scenario innovation. It proposes innovative directions such as sensor technology transfer, material innovation, and modular functional design, aiming to upgrade smart belts from "sub-health monitoring" to "proactive health management," providing an effective solution for lumbar health management.*

Keywords: *smart belt; lumbar spine health; real-time monitoring; machine learning; telemedicine*

1. Introduction

With the accelerating pace of modern life, the health problem of the lumbar spine has become increasingly prominent. According to the Lancet-Rheumatology, the number of global patients with low back pain has reached 619 million, and it is expected to increase to 843 million by 2050. In China, more than 200 million people are at risk of lumbar spine health, and the detection rate of lumbar intervertebral disc herniation in working people aged 25-39 is as high as 13.93%. There are many problems in the traditional lumbar spine health management mode, and it is difficult to achieve precise prevention and personalized rehabilitation. The emergence of intelligent belt brings hope for solving these problems, but its development is faced with bottlenecks such as difficult data collection, low sensor accuracy and short battery life. This paper aims to break through these limitations through technology migration and scene innovation, and deeply explore the relevant technical feasibility, market demand, user portrait and solutions.

In the research and development of smart belts, many scholars have made explorations.Zheng Gang and other scholars proposed a fall detection based on a belt and suggested using the MPU6050 six-axis accelerometer sensor to monitor the posture of the elderly[1][2]. Yan Lijuan and other scholars have conducted research on an intelligent alarm belt system for accidental falls [1][3]. Yu Zhen proposed a blind navigation belt with ultrasonic modules for distance measurement and infrared modules for obstacle detection, which alerts the blind through voice and tactile means [1][4]. Ruan Taiyuan proposed a belt with human posture monitoring functions [1][5]. Zhou Liping proposed a belt with human center of gravity trajectory and tilt angle measurement functions [1][6].

During the research process, we used a wearable belt to place sensors at appropriate positions for data collection. The piezoelectric pressure sensor's output voltage was transmitted to the microcontroller via a data conversion module. Through experiments, we identified the lumbar posture corresponding to voltage changes. Combined with data from accelerometers during patient movement, this approach enabled more precise diagnosis of sub-health issues in the lumbar region. We then used a wireless communication module to transmit the relevant data to software applications for monitoring and statistical analysis. Finally, we established a machine learning-based prediction model for lumbar sub-health based on the collected data.

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2. Problems existing in the process of intelligent belt exploration

2.1 Data acquisition section

Piezoelectric pressure sensors and accelerometers have issues in data collection. Piezoelectric sensors are susceptible to interference from temperature and humidity, leading to data drift. The placement of sensors varies due to individual differences, affecting data quality. Additionally, signal noise is present during dynamic movements; if the sensor shifts or is affected by other signals, it impacts data accuracy.

2.2 Data conversion module

The data processing capacity of the microcontroller is limited, and data loss or delay will occur when the sampling rate is too high. The unreasonable design of the amplifier and filter circuit for the sensor output signal will affect the accuracy of the data. The compatibility problem between the microcontroller and the wireless module will also lead to unstable data transmission, which affects the overall performance of the smart waist belt.

2.3 Posture recognition stage

Pose recognition requires a large amount of labeled data to train models, which must be completed by professionals, making it time-consuming and costly. Different users have significant differences in their movement patterns, leading to insufficient model generalization capabilities and difficulty in accurately identifying different user poses. Moreover, existing data fusion methods for piezoelectric sensors and accelerometers are not effective enough, resulting in inaccurate pose recognition.

2.4 Data gaps

The current data volume is insufficient, lacking population data of different body types, ages, and genders, making it difficult to comprehensively cover sub-health conditions, which affects the accuracy of model predictions. The lack of long-term data makes it hard to analyze the changing trends of lumbar issues. The gap between laboratory environments and actual usage conditions also leads to insufficient data in real-world settings, impacting the accuracy and practicality of the model.

3. Technical feasibility analysis

3.1 Feasibility of sensor technology migration

3.1.1 Technical adaptability analysis

The 3D printing high-precision sensor technology of Liquid Crystal Elastomer (LCE) used in smart wristbands has the characteristics of flexible deformability, high SNR (≥60dB) and micro-strain sensing (0.1% resolution). When migrating to the belt scene, the following adaptation problems need to be solved:

Mechanical Fit: The radius of curvature at the waist (averaging 15-20 cm) is significantly larger than that at the wrist (5-8 cm). It is necessary to optimize the sensor array layout through finite element simulation and adopt a gradient stiffness design (such as serpentine interconnection structure) to achieve surface adhesion, ensuring that the sensors fit tightly against the waist for accurate data collection.

Signal stability: The range of motion of the lumbar muscle group (such as the skin stretch rate can reach 8% when bending) is much higher than that of the wrist. Motion artifacts can be compensated by multi-modal data fusion (piezoelectric + capacitive sensing), and the signal stability and accuracy can be improved by referring to the PPG signal dynamic baseline correction algorithm.

Power consumption control: Compared with wristband single-point monitoring, the belt needs to cover the L1-L5 vertebral body area (about 5x8cm^2 sensing area). It is recommended to use time-sharing power supply strategy and only start full array sampling when the posture changes are triggered. The power consumption can be reduced by 40% and the battery life can be effectively extended.

3.1.2 Verification path

Construct a lumbar bionic motion platform (simulating flexion, lateral bending, and rotation) to compare the consistency of posture recognition between LCE sensors and medical surface

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electromyography (sEMG) devices, with a target Kappa value of ≥0.85. If the Kappa value does not reach 0.85, further optimization of sensor array layout or improvement of data fusion algorithms will be pursued to enhance the accuracy of posture recognition.

3.2 Feasibility of functional modular design

3.2.1 System architecture design

The three-level modular architecture of "sensing layer-edge computing layer-interaction layer" is proposed:

Sensing layer: Health monitoring module: integrated medical grade infrared thermopile (body temperature ±0.2℃ accuracy) and optical heart rate module (MAX30102), reuse accelerometer data to achieve calorie estimation, and comprehensively monitor the user's health status.

Motion auxiliary module: The six-axis IMU (BMI270) is used to construct the attitude quaternion model, and the piezoelectric array data fusion is combined to realize the lumbar curvature monitoring (resolution 1°), so as to provide users with attitude monitoring and guidance during the motion process.

Edge computing layer: Deploy lightweight TinyML model (TensorFlow Lite Micro) to realize local posture classification (LSTM network) and abnormal vibration warning (FFT peak detection), so as to timely detect users 'abnormal posture and movement, and ensure users' health and safety.

Interaction layer: Real-time posture correction is realized through the tactile feedback unit (linear resonant actuator, LRA), and bluetooth Mesh networking (nRF5340 chip) is supported to connect with smart phones, so that users can receive reminders and view data conveniently, realizing intelligent interaction.

3.2.2 Control of R&D complexity

Interface standardization: Define a unified data bus (compatible with I²C/SPI), and use FPC connector to achieve plug-and-play hardware, which reduces the complexity of hardware development and improves the compatibility and scalability between modules.

Function decoupling: The health monitoring and exercise assistance modules are powered independently (dual battery compartment design), and the coupling degree is reduced through event-driven architecture (EDA) so that each module can operate independently without interference, improving the stability and reliability of the system.

3.2.3 feasibility verification

Using the MBSE (Model-Based Systems Engineering) method, a multiphysics joint simulation model (electromagnetic-thermal-force coupled) was established in Simulink to pre-validate module interaction logic and power budget (target standby duration ≥ 72h). Through simulation analysis, issues in the design can be identified early, optimizing system design to ensure that the performance of the smart waistband meets actual usage requirements.

3.3 Existing Data Processing and Analysis Techniques

3.3.1 Data Processing Techniques

Filtering and Noise Reduction: During the data acquisition process, sensor data may be subject to noise interference. Digital filtering techniques can be employed to remove noise, thereby enhancing the quality and stability of the data and ensuring more accurate subsequent analysis results.

Feature Extraction: Extracting feature parameters related to sub-health of the lumbar spine from the vast amounts of raw data collected, such as the amplitude and frequency of pressure changes, and the peak and mean values of acceleration. These features can more directly reflect the state of the lumbar spine and provide key information for diagnosis and prediction.

3.3.2 Data Analysis Techniques

Cloud Computing and Big Data Technology: By leveraging a smart belt to collect data and uploading this data to cloud servers, it becomes possible to utilize big data technology and cloud computing to conduct analysis and mining on a vast amount of data. This process enables the provision of more in-depth and comprehensive health and sports-related recommendations for users. Meanwhile, cloud computing technology can achieve remote storage and backup of data, ensuring the security and

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reliability of the data.

Machine Learning Algorithms: Establishing lumbar sub-health degree prediction models based on machine learning using the collected data. Through model training, the models can automatically learn patterns and features in the data to accurately predict the sub-health status of the lumbar spine. For example, algorithms such as decision trees, support vector machines, and neural networks can be used to train and optimize different feature combinations, thereby improving the accuracy and reliability of predictions.

Data Visualization: Presenting the processed and analyzed data in the form of intuitive charts and graphs within software applications, making it easier for users and medical staff to view and understand. Data visualization technology can help users gain a clearer understanding of their lumbar spine health status and assist doctors in conducting remote diagnoses and tracking the progression of conditions.

3.3.3 Integration of Artificial Intelligence and the Internet of Things

In the future, the smart belt can be deeply integrated with artificial intelligence and the Internet of Things (IoT) technology. By establishing connections with various other types of intelligent medical devices and systems, it can achieve the purpose of data interaction and sharing, thereby providing users with more comprehensive and personalized services.For example, integrating data from smart belts with electronic medical record systems and telemedicine platforms allows doctors to formulate more precise treatment plans for patients by considering information from multiple sources.

4. Feasibility Analysis of Materials

With the rapid development of smart wearable devices, smart belts, as an important tool for lumbar health management, have their material selection directly affecting product performance, user experience, and market competitiveness. The feasibility analysis of materials needs to be carried out from multiple dimensions such as mechanical compatibility, signal stability, biocompatibility, environmental adaptability, and cost-effectiveness. Combining the actual needs of smart belts, the innovation directions and technical feasibility of their materials are explored.

4.1 Material Requirements Analysis of the Smart Belt

4.1.1 Feature Requirements

The smart belt needs to meet multiple functions such as health monitoring, sports assistance, and comfortable wearing. The material selection needs to take into account the following characteristics:

Flexibility and deformability: Conform to the human waist curve (radius of curvature 15-20cm) and adapt to dynamic movements such as bending and rotating.

High signal-to-noise ratio: Reduce environmental interference (such as temperature and humidity changes, electromagnetic noise) to ensure the accuracy of sensor data.

Biocompatibility: Long-term wearing needs to avoid skin allergies or compressive injuries. Breathability and antibacterial performance are crucial.

Lightweight and durability: Reduce user burden, improve battery life (target standby time ≥72 hours), and resist daily wear and tear.

4.1.2 Technical Adaptation Requirements

Sensor integration: Compatible with various sensing technologies such as piezoelectric, capacitive, and optical sensors.

Energy management: The material needs to support flexible batteries or energy harvesting technologies (such as piezoelectric power generation).

Signal transmission: High conductivity materials optimize signal transmission efficiency and reduce power consumption.

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4.2 Evaluation of Candidate Materials

4.2.1 Flexible Sensing Materials

Liquid crystal elastomer (LCE): Achieving high-precision micro-strain sensing (with a resolution of 0.1%) through 3D printing technology, with a signal-to-noise ratio of ≥60dB, suitable for dynamic pressure monitoring. Simulations show that the sensor array using LCE has a fitting degree of 95% at a curvature radius of 15cm, which is better than traditional silicone materials (with a fitting degree of 80%). However, LCE is sensitive to temperature and humidity, and surface coatings (such as polyimide films) are needed to reduce drift errors. It is suitable for the core modules of lumbar curvature monitoring and posture recognition.

Graphene-based composite materials: With high conductivity (conductivity of \(10^6\) S/m), ultra-thinness (<1μm), and high bendability (>100,000 cycles). They play a role in signal transmission, and as electrode materials, they can reduce signal attenuation and enhance the output stability of piezoelectric sensors. As a multifunctional integrated material, combined with MXene materials, it can achieve self-heating functions, suitable for outdoor scenarios in low-temperature environments. However, the cost is relatively high (about three times that of traditional materials), and the mass production process is not yet mature.

4.2.2 Structural Support Materials

Shear thickening fluid (STF): In its normal state, it is liquid, but it hardens instantly (with a viscosity increase of \(10^3\) times) when impacted, with military-grade impact resistance. It has a protective function and can be integrated into the belt's interlayer to absorb the impact force of a fall (with a triggering threshold of ≥50N), reducing the risk of lumbar injury. For lightweight improvement, polyurethane-based STF is used instead of carbon fiber, reducing the weight by 40% and meeting the civilian market demand. However, the fluid distribution may become uneven after long-term use, and microcapsule encapsulation technology is needed to enhance stability.

Shape memory alloy (SMA): It can recover its preset shape under temperature or electrical stimulation, dynamically adjusting the belt's fit.

It can automatically adjust the tightness according to the user's body shape, solving the problem of sensor displacement. Moreover, using Joule heating requires only 0.5W power, which is suitable for low-power scenarios. However, the cycle life is limited (about 5000 times), and the alloy composition needs further optimization.

4.2.3 Surface Contact Materials

Antibacterial textile composite materials: With silver ion coatings or graphene embedded fibers, the antibacterial rate is ≥99.9%, and the breathability rate is >5000g/m²/24h. They can be worn for a long time, reducing skin problems caused by sweat accumulation and enhancing user comfort. Conductive fibers (such as silver-coated nylon) can be used to shield external electromagnetic interference and achieve the function of suppressing signal interference.

Hydrogel patches: With a high water content (≥80%) and ultra-elasticity (with a tensile strength of >500%), they have medical-grade biocompatibility. Coupled with sensors, they can be used as an interface layer to improve the uniformity of contact between piezoelectric sensors and the skin, reducing motion artifacts. Modular patches support user self-replacement, extending the product's service life.

4.3 Prediction of Material Innovation Directions

4.3.1 Heterogeneous Integration of Multiple Materials

Achieving functional zoning through multi-layer composite structures:

Inner layer: Hydrogel patches + LCE sensors, optimizing signal acquisition.

Middle layer: STF impact-resistant layer + SMA adjustment module, balancing protection and dynamic conformance.

Outer layer: Antibacterial fabric + graphene electrodes, ensuring comfort and signal transmission.

4.3.2 Self-powered Material Systems

Piezoelectric fiber fabric: PVDF-TrFE copolymers are woven into a mesh structure to generate

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electricity using the mechanical energy of waist movements (with an output power of 0.1mW/cm²), which can power low-power sensors.

Flexible solar cells: Perovskite materials (with PCE>20%) are integrated on the outer side of the belt to support battery life in outdoor scenarios.

4.3.3 Smart Responsive Materials

Photochromic fibers: Changing color according to the intensity of ultraviolet light to remind users to protect against sunburn.

Thermosensitive phase change materials: Absorbing heat at high temperatures (with an enthalpy value of ≥150J/g) to maintain a stable temperature in the wearing area.

5. Market demand and user portrait analysis

5.1 Health management needs: Chronic disease surveillance is driving market growth

In 2024, the Chinese waist belt market size has reached 2.245 billion yuan, with smart waist belts becoming the main driver of growth due to their built-in sensors and health monitoring functions. As people's health awareness increases, the demand for lumbar health and chronic disease management has significantly risen, especially in improving the level of chronic disease prevention literacy (32.77%), which has driven the market's focus on features such as dynamic pressure monitoring and posture correction. For example, smart waist belts can provide fatigue warnings for sedentary individuals by real-time monitoring of lumbar curvature and movement trajectories, reducing the risk of herniated discs, aligning with the Healthy China strategy's advocacy for chronic disease prevention and control.

5.2 Data-driven precision intervention

The demand for medical-grade data is growing, and smart belts, combined with temperature and heart rate monitoring modules (such as MAX30102 optical sensors) and AI algorithms, can generate personalized health reports and push customized rehabilitation plans via an APP. This "monitoring-analysis-intervention" closed-loop model is gradually replacing traditional passive protective products, providing users with more precise and effective health management services [7].

5.3 Needs of special groups: innovation in the civilianization of military technology

5.3.1 Conversion of protection function

The military belt uses impact-resistant materials (such as shear-thickening fluid STF) and ergonomic design, which can be adapted for civilian safety protection functions. For example, piezoelectric sensors detect fall impact forces, triggering airbag deployment or emergency call mechanisms, suitable for elderly individuals and outdoor workers. Such features have a market penetration rate of less than 5% in the civilian sector, indicating significant potential for development [8].

5.3.2 Occupational scene adaptation

For high-risk occupations such as soldiers and firefighters, smart belts can integrate environmental sensors (such as temperature and humidity, gas detection) to provide real-time feedback on work environment data and link with the backend early warning system. Civilian improvement directions include lightweight design (polyurethane-based STF replacing carbon fiber) and dynamic conformal structures (shape memory alloys adjusting fit), enhancing daily wearing comfort and meeting the diverse needs of special occupational groups during their work [9].

6. Policy-driven and technology convergence trends

6.1 Policy-driven: Standardization and sustainability trends

The "Healthy China" strategy leads industry standards. As the "Healthy China" initiative deepens, smart wearable devices, as key components of health monitoring, will receive more policy support. For instance, the state has issued the "Opinions on Promoting the Transformation and Upgrading of the Garment Industry," which explicitly supports the research and development of smart wearable devices

ISSN 2522-3488 Vol. 9, Issue 2: 1-8, DOI: 10.25236/IJNDES.2025.090201

and brand building, promoting product upgrades towards higher-end, smarter, and greener options. In the future, the industry may further establish medical-grade data standards (such as blood pressure and heart rate monitoring accuracy specifications) and strengthen product certification through regulations like the "Medical Device Supervision and Administration Regulations" to ensure the reliability and privacy security of health data. However, during the implementation of these policies, challenges may arise, such as technical difficulties in standard setting and regulatory challenges in enforcing regulations, which require joint efforts from all parties to address.

6.2 Technology integration: Deep application of AI intelligent agent (AIAgent)

6.2.1 Personalized health management

AIAgent will integrate multimodal sensor data (such as piezoelectric pressure, IMU motion trajectories) to analyze the user's lumbar posture and movement habits through federated learning models, generating dynamic health recommendations. For example, when prolonged sitting is detected, the belt can provide haptic feedback to remind the user to adjust their posture and simultaneously push customized rehabilitation training plans. The IDC report points out that by 2025,70% of enterprises will integrate AIAgent, whose natural language processing capabilities support voice interaction and real-time answers to users' health questions. Federated learning models are a distributed machine learning technique that allows participants to collaboratively train models without sharing raw data, protecting user data privacy while fully leveraging multi-party data to enhance model performance [10][11].

6.2.2 Swarm intelligence and collaborative decision making

Referring to the concept of "group intelligence," in the future, belts may be embedded with multiple AIAgent units working together: one agent is responsible for real-time monitoring of physiological data, another analyzes exercise risks, and a third interacts with cloud-based medical platforms to achieve end-edge-cloud collaboration. For example, in an exercise scenario, the group of agents can predict muscle strain risks and work in conjunction with the exercise APP to adjust training plans, providing users with more scientific and reasonable exercise guidance [12].

6.2.3 Adaptive learning and model optimization

By deploying lightweight models (such as TensorFlow Lite) through edge computing, the belt can perform data preprocessing locally, reducing cloud dependency. At the same time, using incremental learning techniques, the model can dynamically optimize based on long-term user data, adapting to individual differences. For example, for patients with lumbar disc herniation, the model can learn their rehabilitation cycle characteristics and provide staged intervention strategies to improve recovery outcomes.

7. Conclusions

The development of smart belts should not be limited to single hardware innovation but should aim at becoming a "digital interface for human health," deeply integrating flexible electronics, edge intelligence, and medical expertise. By fostering deep collaboration among industry, academia, and research, and jointly building cross-industry standards, we can break through the current "Darwinian dead sea" of data and technology, truly achieving an upgrade from "sub-health monitoring" to "proactive health management."For cross-industry standardization, a unified standard-setting process framework should be established, clearly defining the responsibilities and divisions of labor in each industry to ensure the scientific validity and applicability of the standards. Through these measures, we can promote the healthy development of the smart belt industry and provide more effective solutions for people's lumbar spine health management.

Acknowledgements

This study is funded by the College Students' Innovation and Entrepreneurship Training Program of Southwest Minzu University (Project No.: S202410656067), and we express our sincere gratitude.

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ISSN 2522-3488 Vol. 9, Issue 2: 1-8, DOI: 10.25236/IJNDES.2025.090201

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