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Promoting Rehabilitation Using a Multimodal Internet of Things-Based Patient Monitoring System in a Smart Hospital

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ABSTRACT Objective: Continuous monitoring of patients' physical and psychological status using wearable sensors and Internet of Things platforms may enhance rehabilitation. We aimed to assess the feasibility of an Internet of Things-based smart hospital system integrating multi-source data to support individualized rehabilitation in patients with gait disturbances. Methods: We conducted a single-center feasibility study at Yongin Severance Hospital, Korea, including 15 inpatients with subacute central nervous system injuries (mean age, 60.9±16.7 years). The system integrated smart insoles, smart bands, real-time location system data, and mobile application data into the electronic medical record. Gait parameters, including step count, walking distance, gait speed, stride length, and symmetry, were measured during self-exercise. The app collected self-reported scores on pain, anxiety, depression, appetite, sleep, and general condition. Compliance, patient satisfaction, and nurses' qualitative feedback were analyzed descriptively. Results: Monitoring lasted 17.0±12.6 days. Patients averaged 7,323±5,520 steps/day and walked 3,910±3,198 m/day; 87% showed reduced stride length and 27% had marked gait asymmetry. Application-based symptom monitoring enabled tailored interventions, including medication adjustments and referrals. Smart band data were sometimes incomplete owing to recording errors. Operational challenges included battery depletion, data transfer interruptions, and device registration errors. Overall satisfaction averaged 4.28/5; comfort rated the highest, durability the lowest. Nurses valued real-time condition detection and improved self-report honesty but noted increased workload. Conclusion: Implementing an Internet of Things-based system that integrates wearable and self-reported data into an electronic medical record is feasible in inpatient rehabilitation, facilitating individualized feedback and clinical decision-making while maintaining high patient adherence and satisfaction.

INDEX TERMS Digital technology, electronic health records, Internet of Things, rehabilitation, wearable electronic device.

Clinical Impact—This study shows the feasibility of an IoT-based smart hospital system integrating multi-source data into EMRs, enabling personalized rehabilitation, improving clinical decision-making, and supporting scalable digital healthcare models.

I. INTRODUCTION

THE evolution of digital technology and wireless networks has accelerated the digital transformation of healthcare systems. Wearable sensors and "Internet of Things" (IoT) technologies have enabled intelligent recognition, tracking, monitoring and management of patients'

medical conditions in real-time [1], and high-density and high-speed networks have facilitated data communication and integration across diverse hospital environments [2], [3]. Smart hospitals based on IoT technology not only improve work efficiency but also enhance patient safety and satisfaction.

Using wireless sensors to automatically record patient conditions in electronic medical records (EMR) allows for early detection and minimizes the likelihood of severe complications. Wireless vital sign monitoring systems can shorten the time needed to measure patients' vital signs and improve the quality of rapid response systems [4]. Several algorithms have been developed to detect asymptomatic atrial fibrillation, which is one of the major risk factors for cardioembolic stroke, based on data collected from wearable sensors [5], [6], [7]. Furthermore, mobile applications (apps) were used for stress relief as well as symptom monitoring for quarantined patients during the coronavirus disease 2019 (COVID-19) pandemic [8].

Recent technological advancements have enabled both the tracking of complex parameters, such as sleep patterns and physical activity through wearable sensors, as well as the collection of patient-reported outcomes via mobile apps. These additional indicators are increasingly recognized as relevant factors related to complications such as delirium or falls [9], [10]. One study used a real-time location system (RTLS) to show that patients who experienced in-hospital falls tended to exhibit less activity and slower movement speed just before a fall compared to that measured during the early hospitalization period [11]. Moreover, the implementation of wearable activity trackers during hospitalization has been shown to enhance overall physical activity and reduce sedentary behavior [12]. However, the integration of various devices into hospital systems and clinical workflows remains limited owing to several factors, including privacy concerns, data security, technical challenges related to interoperability, and infrastructure requirements within hospitals [13]. In addition, RTLS and smart bands primarily capture gross movement without providing information about its qualitative aspects, which may be critical in understanding the functional status of patients and tailoring rehabilitation strategies to meet their individual needs. Although mobile apps have been shown to be effective tools for monitoring subjective symptoms such as pain and appetite [14], [15], there is a lack of research focusing on the integration of such self-reported data into hospital-based systems alongside sensor-derived activity data.

Previous studies conducted at our institution have shown that an RTLS can be effectively used to control infections and predict falls [11], [16], [17]. Building on this infrastructure, the aim of this study was to expand the system into a more integrated digital platform by incorporating smart insoles and a smart band to capture detailed physical activity data as well as a mobile app for collecting patients' subjective symptom reports. The feasibility of implementing this system was evaluated in patients with gait disturbances requiring comprehensive rehabilitation. Furthermore, the challenges encountered during the implementation of the system were reported, and the perceptions of both patients and healthcare providers regarding the system were explored.

II. METHODS AND PROCEDURES

A. SMART HOSPITAL SYSTEM

Yongin Severance Hospital is a single 17-story building with a total floor area of 111,923 m^2. The institution comprises 708 beds across 33 medical departments, staffed by approximately 200 physicians and 2,000 other employees. An IoT network has been established throughout the hospital, incorporating 5G mobile networks, 5 GHz Wi-Fi, and 1,136 in-ceiling passive Bluetooth Low Energy beacon scanners covering the entire building, as previously described [18].

In this hospital, all patients were assigned an 8-digit patient identification (ID) number upon registration. After obtaining informed consent for data collection, the ward nurse mapped the serial numbers of each digital device to the corresponding patient ID. Data collected from various digital devices are transmitted through gateway servers and integrated into host servers, and an individualized report page was automatically generated within the EMR system, displaying information collected from each of these devices.

In 2021, Yongin Severance Hospital developed an isolation ward to serve as a monitoring solution for patients with COVID-19; this facilitated both the remote collection of vital sign data via contactless devices as well as the self-reporting of symptoms via a mobile app. As the COVID-19 pandemic evolved into the endemic phase, this solution was expanded into a comprehensive IoT-based inpatient monitoring system to support not only patients receiving treatment in isolation wards but also those being managed in general wards [18].

The initial conceptualization phase began in March 2023, followed by iterative storyboard revisions, pilot testing, and system refinement in collaboration with multidisciplinary teams of healthcare providers, hospital information technology personnel, and industry partners. After the implementation of the monitoring system was completed, it was deployed in June 2024, and it was used to monitor 15 patients through March 2025.

The IoT-based inpatient monitoring system consisted of the following three core components (Figure 1):

1. **Data collection** from medical-grade devices and mobile apps;
2. **Data processing and integration** via a smart hospital platform; and
3. **Clinical access** through an EMR-embedded report page.

In the data collection phase, sensor data were obtained from smart insoles, smart bands, and RTLS tags, whereas self-reported symptom-related data were recorded through a mobile app called "Big 4+". These signals were transmitted via gateway scanners to the in-hospital server, where they

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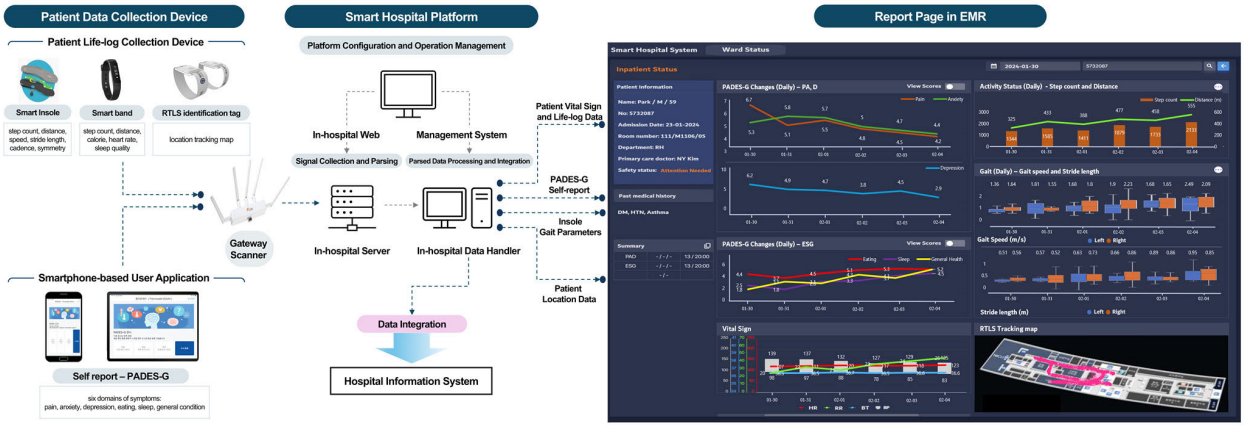

FIGURE 1. Overview of Smart Hospital System based on 5G network in Yongin Severance Hospital: Data is collected from the wireless sensor to the server through the gateway scanner; Numeric parameters are integrated with HIS and EMR; A report page that displays summary of data for each patient is automatically created.

were parsed, processed, and integrated by a dedicated data handler. The integrated data were stored within the hospital information system (HIS) and EMR. The EMR report page provided clinicians with access to each patient's vital signs, life-log metrics, self-reported symptoms, gait parameters, and real-time location information.

B. DIGITAL SOLUTIONS

1) RTLS

The hospital implemented an RTLS (People and Technology, Inc., Republic of Korea) to track the location of patients, property, and medical staff members using ID tags. All inpatients were required to wear these beacon-enabled patient ID tags throughout their stay, beginning on the first day of hospitalization. The reliability and utility of this system in clinical settings have been demonstrated in previous studies [11], [16], [17].

2) SMART INSOLES

The spatiotemporal parameters of patients' gait were recorded using an I-SOL®instrumented insole system (Gilon, Seongnam, Korea), comprising four force-sensing resistors, a three-axis accelerometer (BMA253 digital sensor; Bosch, Gerlingen, Germany), a Bluetooth 4.2 Low Energy module (nRF51822, Nordic Semiconductor, Trondheim, Norway), and a lithium coin cell battery (CR2032) embedded in each insole. Sensor data were sampled at a frequency of 40 Hz and transmitted to an in-hospital server. A total of 14 waveform data streams were collected from each participant and processed in real-time using an in-house algorithm. In brief, the gait cycle was determined based on the timing of peaks detected by the pressure sensors and the y-axis accelerometer. Noise correction was applied using a machine learning model. Gait parameters such as step count, walking distance, walking speed, stride length, and gait asymmetry were subsequently computed. The reliability and validity of the I-SOL®system have been demonstrated in previous studies [19], [20], [21]. In addition, we conducted on-site validation by comparing insole-derived gait parameters with those obtained from a marker-based 3D motion analysis system (VICON MX-T10, Oxford Metrics Inc., Oxford, UK) in 16 healthy individuals (7 men and 9 women; mean age 31.1 $\pm$ 4.4 years). The two methods showed significant agreement, supporting the reliability of insole-based gait analysis (Supplementary Table 1). Previous research using other smart insole systems has also demonstrated the feasibility of utilizing gait and plantar-pressure signals for neurological disorder monitoring [22], [23]. The report page generated by the system displayed both the absolute values for each patient as well as normative values for comparison (Figure 2) [24]. Attending physicians and nurses were able to access the report at any time to establish individualized rehabilitation goals, including improving gait speed, enhancing total walking distance, correcting gait asymmetry, or expanding the range of activity.

3) SMART BAND

Daily physical activity and sleep-related parameters were monitored using an URBAN HR®wearable smart band (Patron, Hwaseong, Korea) equipped with a six-axis accelerometer and a heart rate sensor. The band measured step count, distance traveled, caloric expenditure, and heart rate during activities, and it generated sleep quality scores during nighttime use.

4) MOBILE APP

Patients undergoing treatment were encouraged to self-report the symptoms they experienced using the Big4+ mobile app, which was designed to assess the following six domains: pain intensity, anxiety, depression, eating/appetite, sleep quality, and general condition (Figure 3). Patients could report symptoms at their discretion or respond to push notifications

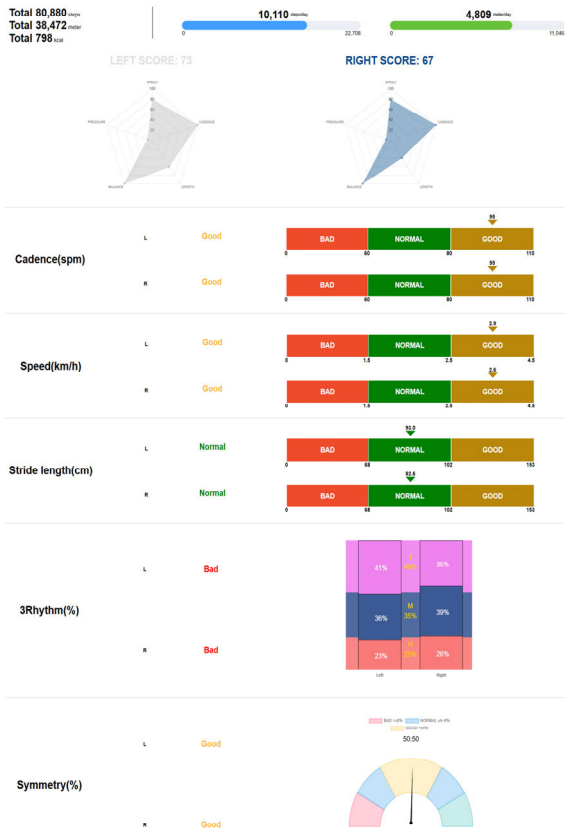

FIGURE 2. Report page presenting gait analysis results derived from data acquired from smart insoles. The graphs compare patient data with normal reference values to facilitate easy identification of abnormalities.

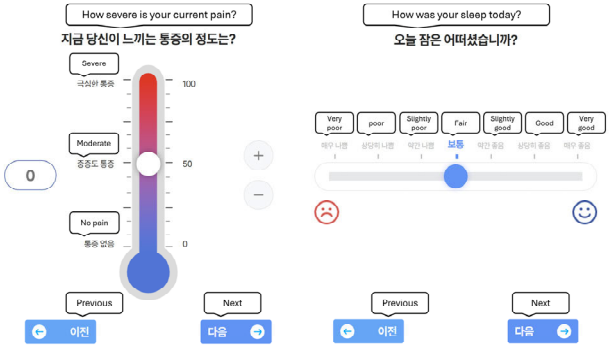

FIGURE 3. Example screens from the Big 4+ mobile application, which collects patient-reported information on pain, anxiety, depression, eating habits, sleep quality, and general condition. Pain and sleep quality are rated on a 0–100 scale, with each screen representing part of the in-app response process.

delivered twice daily, and data were automatically transmitted to the server. The validity of this app-based assessment system has been demonstrated in a previous study, which confirmed its feasibility for the collection of real-time psychosocial and behavioral data [15].

C. PARTICIPANTS

Inpatients who were potentially eligible for the study were carefully selected according to the following inclusion criteria: age $\geq$19 years; patients capable of understanding one-step commands; patients in the subacute phase following central nervous system (CNS) injury (defined as more than 7 days post-onset) requiring gait rehabilitation; and patients in whom ambulation was encouraged to improve function, with a modified Rankin Scale (mRS) [25] of 2–4 at baseline. Patients with any unstable medical condition were excluded from the study, as were those who were expected to be discharged within 1 week, which would have made it impossible to collect sufficient data for analysis.

All patients, independent of the monitoring, were prescribed physical and occupational therapy tailored to their individual neurological and functional levels, and they were also instructed to perform exercises on their own, outside of therapy sessions, to reduce sedentary behavior, especially considering that rehabilitation sessions were not conducted over weekends. To minimize confusion regarding the data being collected, wearing the smart insoles was recommended only during self-exercise sessions.

Satisfaction with the monitoring system was evaluated at the time of discharge of each patient based on a five-point Likert scale, with the assessment encompassing the following 13 domains: 1) physical dimensions; 2) device weight; 3) adjustability; 4) safety; 5) durability; 6) ease of use; 7) comfort; 8) effectiveness; 9) service delivery; 10) repairs and maintenance; 11) professional services; 12) follow-up services; and 13) overall satisfaction. In addition, structured qualitative feedback was collected from ward nurses using a brief post-deployment questionnaire that included open-ended questions. The questionnaire was designed to explore their experience with using wearable sensors in a clinical setting, the perceived benefits, and implementation challenges to evaluate the feasibility and usability of the system from a clinical staff perspective.

D. ETHICAL CONSIDERATIONS

This study was initially approved by the Institutional Review Board and Ethics Committee of the Yongin Severance Hospital in 2021 and subsequently re-approved with a revised protocol on September 5, 2025 (IRB No 9-2025-0122). Written informed consent was obtained from all participants prior to enrollment.

E. DATA QUALITY AND DEVICE VERIFICATION

Data quality and device connectivity for all devices was verified daily by the research team, and the collected data were continuously monitored throughout the day to identify any clinically implausible values (e.g., heart rate $<$ 30 or heart rate $>$ 250). If a metric was completely missing, we investigated whether it was due to a device malfunction, lack of device use by the participant, or network connectivity issues.

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Metrics obtained from the devices were reconciled to verify the proper functioning of the device algorithms. For example, the distance recorded by the smart band was checked to ensure it did not differ by more than 20% from the value calculated by multiplying the step count by the average adult step length of 0.63m [26]. Technical issues and human errors encountered during monitoring were documented and categorized into three domains, including device-related problems, data acquisition/processing issues, and user errors.

F. DATA ANALYSIS

Descriptive analyses were performed to summarize the demographic characteristics of the participants. Statistical analyses were conducted to evaluate compliance, data completeness and physical activity.

The primary feasibility endpoint was patient compliance, which was calculated as the number of days with recorded data divided by the total number of days the device was provided. A compliance rate of $\geq$ 80 % was considered the minimum threshold for acceptable feasibility.

Clinically implausible values and data that failed reconciliation checks were flagged. As this study aimed to assess the feasibility of the system, no data were removed or imputed. Data completeness was calculated as the proportion of valid data points obtained for each parameter from the wearable devices and the mobile app across all monitoring days, with a success threshold of $\geq$ 80%. Smart band data were excluded from the final analysis because heart rate values of 0 were recorded in all participants, rendering the measurements unreliable.

For each participant, daily step counts, walking distance, gait speed, and stride length were averaged over the monitoring period. Group-level means across the 15 participants were subsequently calculated for each parameter. We also compared gait parameters before and after monitoring to assess improvements. Gait data from the day after monitoring initiation and the day before monitoring completion were used for analysis, as measurements on the first and last days were often incomplete due to partial monitoring. Normality and homogeneity of variance were tested prior to comparison, and either a paired t-test or Wilcoxon signed-rank test was applied.

Satisfaction ratings were summarized using mean values for each item. Technical issues and human errors encountered during monitoring were documented and categorized into three domains, including device-related problems, data acquisition/processing issues, and user errors.

III. RESULTS

A. CLINICAL CHARACTERISTICS

A total of 15 patients who required gait rehabilitation after neurological injury were included in the study (Figure 4). The clinical characteristics of the 15 participants are presented in Table 1 and Supplementary Table 2. The mean patient age was 60.9±16.7 years. At the start of the

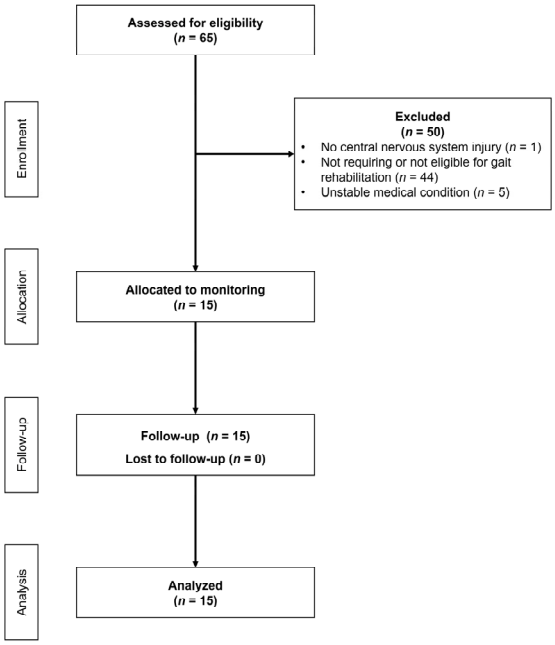

FIGURE 4. Participant flow diagram.

monitoring period, the duration of time since disease onset was 28.7±18.4 days. The mean duration of the hospitalization period was 36.9±17.7 days. All patients exhibited moderate disability, requiring some help but being able to walk without assistance, with a mean mRS of 3.33±0.62. Two patients presented with non-fluent aphasia, characterized by impaired spontaneous speech production with relatively preserved comprehension. The average monitoring duration using the smart hospital system was 16.9±12.4 days. The overall average compliance was 97.7±4.1%, which exceeded the predefined success threshold of 80%, meeting the primary feasibility endpoint. Similarly, data completeness was 100%, except for the smart band, which will be described later.

B. GAIT-SPECIFIC MONITORING VIA SMART INSOLES

Smart insoles were used to collect data related to gait parameters. The participants walked 7,323±5,520 steps daily, covering a distance of 3,910±3,198 m. Patients' in-hospital activity area was recorded using the RTLS, and the data were cross-checked for accuracy. Thirteen (86.7%) patients had a stride length shorter than the normal reference value (<110 cm) [24], with a mean stride length of 100.02±9.20 cm across all participants. The mean gait symmetry across participants was 6.46±6.18 %. Four (26.7%) patients exhibited severe gait asymmetry (>10%). During multidisciplinary rounds, the medical staff reviewed the gait parameters collected via the smart insoles and provided individualized feedback on ways to improve gait patterns and exercise levels. Rounds conducted on Mondays specifically emphasized feedback based on weekend activity and gait patterns, and goals were adjusted for the upcoming week. At discharge,

TABLE 1. Clinical characteristics of participants.

ID	Age/Sex	Main diagnosis	Time since disease onset (days)	Initial mRS	Follow-up mRS	Monitoring period (days)	Compliance (%)
P1	72/M	Infectious spondylitis	69	4	3	7	86
P2	68/M	Autoimmune encephalitis	36	3	2	12	100
P3	77/F	Lt. basal ganglia infarction	27	4	3	7	100
P4	61/M	Rt. basal ganglia infarction	28	3	2	8	100
P5	65/M	Rt. frontal ICH	40	3	2	10	100
P6	68/M	Lt. MCA infarction	12	3	2	29	93
P7	70/M	Rt. basal ganglia infarction	10	4	3	53	98
P8	81/F	Rt. ACA infarction	27	4	2	12	100
P9	83/F	Bilateral post cerebral infarction	21	4	2	15	100
P10	35/M	Lt. basal ganglia infarction	12	3	2	7	100
P11	68/M	Multiple embolic infarction	25	4	3	19	100
P12	42/M	Cervical myelopathy	43	3	3	15	93
P13	42/F	Cervical myelopathy	61	2	2	27	96
P14	32/F	Rt. basal ganglia infarction	12	3	2	24	100
P15	49/M	Rt. MCA infarction	8	3	2	8	100

mRS, modified rankin scale; LOS, length of stay; ICH, intracerebral hemorrhage; MCA, middle cerebral artery; ACA, anterior cerebral artery.

the mean mRS score had improved to 2.33±0.49, indicating slight disability but still maintaining the capacity for independence while performing activities of daily living. A pre–post comparison of gait parameters during the monitoring period demonstrated significant improvements in steps, distance, speed, and stride length (Table 2).

TABLE 2. Pre–post comparison of gait parameters during monitoring period.

Gait parameters	Baseline	End of monitoring	p-value
Steps	6941±6072	8181±5891	0.041 *
Distance (m)	3608±3431	4494±3523	0.026 *
Speed (km/h)	2.73±0.53	3.03±0.64	0.014 *
Stride length (cm)	96.33±13.13	104.00±10.34	0.025 *
Symmetry (%)	7.26±6.01	5.31±5.04	0.135

Values are presented as mean ± SD; * $p<0.05$

C. PATIENT-REPORTED SYMPTOM MONITORING AND SUPPORT VIA MOBILE APP

Self-reported data of the symptoms experienced by the participants were collected via the mobile app, including information on pain intensity, anxiety, depression, eating/appetite, sleep quality, and general condition. The data were reviewed daily by the medical team during routine rounds. Based on these data, individualized treatment decisions were made regarding medication adjustments, further evaluations needed, and supportive interventions.

The average pain score was 21.3±23.8, and seven (46.7%) patients received analgesics during the monitoring period. Four (26.7%) patients experienced musculoskeletal pain, whereas two (13.3%) patients reported surgical site-related pain. Pain scores were used to assess treatment responses, guide changes in the type or dosage of medication being administered, and inform the patient of appropriate exercise and other interventional modalities (such as transcutaneous electrical nerve stimulation). Among those being prescribed analgesics, six (40.0%) underwent dose adjustment, tapering, or discontinuation based on ongoing score trends, enabling tailored pain management. For example, one participant (P1) had a combination of postoperative pain following spinal surgery and neuropathic pain due to spinal cord injury, and reported a pain score over 60 despite receiving multiple analgesics upon request, including acetaminophen, tramadol, buprenorphine (opioid) and irregular injections of pethidine hydrochloride more than three times a day at the start of monitoring. The attending physician educated the patient about the pathophysiology of postoperative and neuropathic pain, and provided instruction on appropriate stretching, exercise techniques, and proper posture both during physical activity and while in bed. Irregular injections of pethidine hydrochloride were discontinued. One week later, as the pain score did not worsen, buprenorphine was tapered out. Three days after complete discontinuation of buprenorphine, the patient's pain score had not worsened, but the characteristics of the pain had become more neuropathic. Thus, tramadol was replaced with pregabalin, a first-line agent for neuropathic pain based on clinical guidelines [27]. During the following week, the patient's pain score improved to 40, and the

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condition remained stable until the end of the monitoring period.

Regarding mood, the participants reported average scores of 69.5±16.9 and 64.8±25.3 out of 100 for depressive symptoms and anxiety, respectively, indicating a moderate level of subjective emotional distress. Four (26.7%) patients were already being treated with selective serotonin reuptake inhibitors prior to the start of monitoring. Attending physicians reviewed each patient's depression and anxiety scores, and treatment plans were discussed to evaluate the need for emotional support, medication adjustments, or nursing interventions. Notably, one patient who had been prescribed a selective serotonin reuptake inhibitor persistently reported low depression scores on the app, leading to discontinuation of the antidepressant. The patient maintained stable depression scores, supporting the decision to discontinue pharmacotherapy.

The average sleep quality score was 67.9±19.4. Four (26.7%) patients were already being treated with sleep medications at baseline. For those with low sleep scores (below 40) for more than three days, repeated education on sleep hygiene was provided, and pharmacologic adjustments were considered. Three (20.0%) patients who consistently reported poor sleep scores for more than one consecutive week and complained of severe snoring underwent additional evaluation; in all three cases, polysomnography confirmed the presence of severe obstructive sleep apnea, and positive airway pressure therapy was subsequently planned.

The mean eating/appetite score was 74.4±20.1. Nutritional status was assessed based on both subjective appetite trends and actual food intake. When low food intake and poor appetite persisted relative to nutritional requirements, further evaluation of the underlying causes and the use of nutritional supplements were considered. One patient who showed scores below 40 in the eating domain for ≥3 consecutive days was diagnosed with sarcopenia and consequently prescribed essential amino acid supplementation. In the other cases, loss of appetite was determined to have been caused by constipation and was managed with medication.

D. LIMITATIONS of SMART BAND-COLLECTED DATA

Data collected from smart bands were excluded from the primary analysis owing to incomplete measurements and data inaccuracies. For example, in the heart rate monitoring, the minimum heart rate was recorded as zero at least once a day in all participants. As these incidents occurred despite confirmed device usage, they were considered to reflect measurement failures rather than patient non-adherence. Furthermore, regarding sleep quality, sleep scores were captured for only 22.3% of the total monitoring period on average, likely owing to patients not wearing the band during sleep. In many cases, it was determined the devices had not been worn owing to discomfort, forgetfulness, or the need for charging; however, since the specific reason was not consistently documented for each instance, the relative contribution of each factor could not be quantified. In terms of physical activity, nine (60.0%) participants exhibited discrepancies between their walking distances and step counts, with the recorded distances being either excessively low or high relative to the number of steps taken. Thus, derived metrics such as the estimated caloric expenditure were also affected by these inconsistencies.

E. OPERATIONAL ISSUES AND END-USER PERSPECTIVES

In addition to the aforementioned limitations related to the collection of data using smart bands, various unexpected technical issues also arose (Table 3). Device-related problems included the failure to notice battery depletion in both the smart insoles and bands, as well as intermittent lag or unresponsiveness in the mobile app. Regarding data acquisition, the need to renew firewall and in-hospital server access permissions annually and individually for each user led to additional unexpected errors. Furthermore, the system occasionally experienced server overloads, which were mitigated by increasing the Java heap memory allocated to the administrative service from 2 GB to 4 GB. As a battery-conserving feature, the smart insoles were equipped with an algorithm that automatically reduced the frequency of signal transmission when a patient remained in the same location for a period of time (in excess of one hour); however, this led to confusion when attempting to interpret the data, as it became unclear in such instances whether the patient was genuinely inactive, the device was not being worn and had been left elsewhere, or if the connection had been lost. The sensor-based indoor distance tracking exhibited variability and occasional discrepancies in terms of observed or reported patient activities. Lastly, human errors occurred in some instances, such as incorrect participant registration.

TABLE 3. Issues related to data collection during monitoring.

Classification		Issues
Device	Insole	Unnoticed battery depletion
	Band	Unnoticed battery depletion
	Smartphone application	Lag or unresponsiveness
Data	Acquisition	Issues related to firewall and access permission
		Server overload
		Device disconnected
Human error	Participant	Survey loss via mobile application
	Investigator	Participant information registration error

Despite these challenges, the average total satisfaction score was 4.28 out of 5, with a score ≥4 for each individual item (Figure 5). The highest-rated item in the survey was the comfort of the wearable devices and smartphone application, whereas the lowest-rated item was device durability, indicating the need for improvement in the insole's battery life and hardware components to enhance long-term monitoring.

Some nurses (n = 3) indicated that they appreciated that the smart hospital system helped them quickly detect changes in their patients, which was especially useful given the frequent

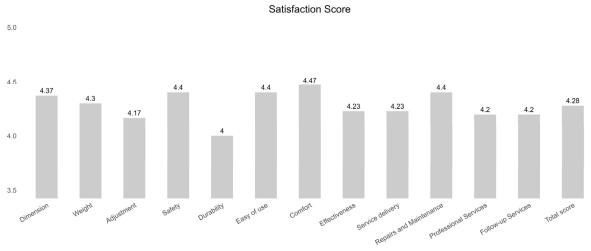

FIGURE 5. Results of the satisfaction survey regarding the gait monitoring system using the instrumented insoles and RTLS. Each value represents the average score from responses of 15 participants in the survey conducted on a 5-point Likert scale.

handovers that occur in the three-shift system. They also found that the self-report tools allowed patients to report symptoms more honestly and at their convenience. However, learning to use new devices added to their workload. Regular education for patients and caregivers, as well as ensuring consistent charging of the devices, were seen as necessary but burdensome tasks that require further improvement.

IV. DISCUSSION

In this study we investigated the real-world feasibility of integrating multi-source digital health data into clinical workflows. The findings confirmed that data collected from various digital devices could be successfully linked to the HIS and transferred to the EMR system, and such data could be helpful in supporting physical rehabilitation strategies and in monitoring psychological aspects of recovery such as emotional well-being. However, certain practical issues must be overcome to improve usability from both patient and staff perspectives.

The development of mobile health apps to support clinical care has accelerated, as they have been shown to be beneficial in facilitating communication within and between health care teams and in guiding clinical decision-making [28]. However, most of the solutions developed to date have focused on chronic internal medicine conditions such as diabetes and hypertension [29], [30]. Moreover, most existing studies have relied on a single type of digital input—typically a mobile app—without integrating data from multiple digital sources. By contrast, in the present study, we implemented a multimodal digital system tailored to patients requiring comprehensive rehabilitation. One of the greatest barriers to the successful implementation of systems that incorporate digital health data is fostering effective collaboration among stakeholders, including both clinical and non-clinical staff, with diverse and sometimes conflicting interests. To address the legal, technical, and financial issues that inevitably arise, it is essential to build a shared understanding of the clinical value of smart systems that incorporate unfamiliar data types, such as gait patterns or factors reflecting emotional states. Establishing such a consensus is a critical first step toward the successful integration of these systems into real-world therapeutic workflows. In our experience, clearly defining and assigning responsibilities at all levels, from system planning and set-up to day-to-day operations, was challenging. Repeated discussions were necessary to coordinate the integration of multiple devices with differing requirements for technical management, patient-facing implementation, and data governance. Differences in departmental priorities and decision-making processes have led to delays and frequent revisions to system planning. Furthermore, close collaboration with the companies who supply equipment and network infrastructure was necessary to address errors and reduce costs. Ultimately, the effectiveness of such systems depends less on the sophistication of individual technologies and more on the ability to align diverse institutional actors around shared goals and responsibilities.

Personalized feedback based on individual motor deficits has been shown to play a critical role in optimizing motor learning and functional recovery in patients who have experienced CNS injuries [31], [32]. It is important to recognize that psychiatric symptoms such as anxiety, depression, and insomnia are highly prevalent in this patient population, and such factors can substantially affect rehabilitation outcomes [33], [34]. Despite their clinical significance, comprehensive and continuous monitoring of these symptoms remains challenging in routine practice. Cognitive and language impairments associated with CNS injury can also hinder the collection of information directly from patients. The results confirmed that this smart hospital system can facilitate precise evaluations of patients' conditions and provide care for their mental and physical health in a data-driven manner. By delivering quantified, visual feedback on patients' gait abnormalities, the system allowed them to actively engage in exercise training. Furthermore, systematic sharing of data pertaining to psychiatric symptom severity and longitudinal trends offers patients opportunities for self-monitoring, a process that is known to enhance motivation and adherence to treatment paradigms [35], [36]. The integration of these functionalities within the existing hospital infrastructure enables seamless clinical implementation and underscores the system's scalability across diverse health care settings. This comprehensive digital platform may contribute to improving the quality and effectiveness of rehabilitation for patients with complex neuropsychiatric needs.

Although potential benefits of the smart hospital system were identified, several challenges remain. From a technological perspective, device battery life and recharging issues can affect both the completeness of data collection and the compliance of healthcare providers and patients. In this study, increased patient activity accelerated battery depletion, and the continual monitoring and maintenance of battery levels was burdensome to both patients and nurses. The usability of the smart band was also lower than expected, although this observation was consistent with previous studies that reported challenges related to compliance and data quality in smart band-based monitoring, especially in inpatient or long-term care settings in which overnight adherence tends to be suboptimal [37], [38]. Another remaining challenge

is to quantify the economic benefits of the smart hospital system relative to all human and material resources invested in its implementation, thereby demonstrating its value. The process of shifting toward a digital monitoring environment consumed substantial human resources; for example, personnel had to be assigned to map devices to patient IDs, ensure proper functioning of the devices, and educate patients on proper equipment use. Lastly, as more data are generated, the costs of its collection, processing, and storage continue to increase, leading to conflicts among stakeholders—including patients, healthcare providers, and device companies—over who should bear these costs. Further research is required to determine the appropriate quantity and quality of data to collect. To ensure continuity of care, it would be ideal to apply the same system to outpatient settings as well; however, there are still barriers to linking data inside and outside the hospital network owing to security concerns. Addressing technical, operational, and financial challenges will be crucial for facilitating the successful implementation and widespread adoption of smart hospital systems.

This study has some limitations. First, the sample size was small, limiting both the statistical power and generalizability of the findings. The study employed a single-arm design without a control group, making it difficult to establish causal relationships between variables or to compare outcomes with standard care. Second, the average monitoring duration was relatively short, making it impossible to assess long-term clinical outcomes, including post-discharge continuity and sustained functional recovery. Third, a sensitivity analysis comparing results with and without borderline-quality data was not performed, as all retained datasets met the predefined data completeness criteria and low-quality data were excluded prior to analysis. Fourth, the proportion and timing of clinical interventions triggered by app-based alerts were not quantitatively recorded. Consequently, the actionability of the alert system and its direct translational impact on clinical workflows could not be fully evaluated. Lastly, the economic benefits of the smart hospital system relative to the resources invested into it were not quantified, precluding cost-effectiveness analyses. Full clinical implementation of digital device–based monitoring would require regulatory approval supported by evidence of utility, safety, cost-effectiveness, and a clearly defined reimbursement framework.

V. CONCLUSION

We present a smart hospital system capable of collecting physical activity and patient-reported symptom data from various wearable devices and a mobile app and subsequently integrating them directly into the HIS. The feasibility of the system in supporting individualized rehabilitation planning and providing timely clinical feedback was confirmed, and the patient compliance and reported satisfaction rates were generally favorable. This work illustrates a concrete step toward the clinical translation of digital health technologies by demonstrating how multimodal, seamlessly engineered data can be integrated into clinical workflows and used to support real-time clinical decision-making. Hence, this work is anticipated to pave the way for more extensive research related to patient-tailored rehabilitation programs that evolve from protocol-based to data-driven models and further leverage the clinical potential of wearable technologies. However, further research involving larger and more diverse populations, longer monitoring periods, analyses across stratified data-quality levels, quantification of actionability, and comprehensive cost-effectiveness analyses is needed to fully validate and optimize the system's clinical utility.

VI. CONFLICTS OF INTEREST

The authors have no potential conflicts of interest to declare.

VII. AUTHOR CONTRIBUTIONS

Conceptualization: Na Young Kim. Data curation: Wonhee Lee, Seung-Ick Choi, Kyung Pyo Hong, Yu joo Kang, Huiwoo Yang, Jin Young Park and Na Young Kim. Formal analysis: Wonhee Lee, Seung-Ick Choi and Na Young Kim. Funding acquisition: Na Young Kim. Investigation: Wonhee Lee, Seung-Ick Choi, Kyung Pyo Hong, Yu joo Kang and Huiwoo Yang. Methodology: Wonhee Lee, Seung-Ick Choi and Na Young Kim. Project administration: Na Young Kim. Resources: Jin Young Park and Na Young Kim. Software: Wonhee Lee. Supervision: Na Young Kim. Validation: Wonhee Lee, Seung-Ick Choi and Na Young Kim. Visualization: Wonhee Lee, Seung-Ick Choi and Kyung Pyo Hong. Writing-original draft: Wonhee Lee, Seung-Ick Choi and Na Young Kim. Writing-review & editing: Wonhee Lee and Na Young Kim.

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