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Closing the Wearable Gap—Part VIII: A Validation Study for a Smart Knee Brace to Capture Knee Joint Kinematics

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Abstract: *Background:* Wearable technology is used by clinicians and researchers and play a critical role in biomechanical assessments and rehabilitation. *Objective:* The purpose of this research is to validate a soft robotic stretch (SRS) sensor embedded in a compression knee brace (smart knee brace) against a motion capture system focusing on knee joint kinematics. *Methods:* Sixteen participants donned the smart knee brace and completed three separate tasks: non-weight bearing knee flexion/extension, bodyweight air squats, and gait trials. Adjusted R^2 for goodness of fit (R^2), root mean square error (RMSE), and mean absolute error (MAE) between the SRS sensor and motion capture kinematic data for all three tasks were assessed. *Results:* For knee flexion/extension: R^2 = 0.799, RMSE = 5.470, MAE = 4.560; for bodyweight air squats: R^2 = 0.957, RMSE = 8.127, MAE = 6.870; and for gait trials: R^2 = 0.565, RMSE = 9.190, MAE = 7.530 were observed. *Conclusions:* The smart knee brace demonstrated a higher goodness of fit and accuracy during weight-bearing air squats followed by non-weight bearing knee flexion/extension and a lower goodness of fit and accuracy during gait, which can be attributed to the SRS sensor position and orientation, rather than range of motion achieved in each task.

Keywords: stretch sensors; gait; wearable technology; knee kinematics

1. Introduction

Various wearable devices are commercially available to researchers, clinicians, and healthcare providers, such as physical therapists, athletic trainers, and occupational therapists, for biomechanical assessments and rehabilitative purposes [1–3]. Wearables can include different types of devices comprising inertial measurement units (IMUs) such as accelerometers, gyroscopes, magnetometers, pedometers, and goniometers. Additionally, clothing with incorporated sensor technology presented as "smart garments" aid in quantifying human body joint kinematics [2,4]. Recently, the current team of researchers has developed a smart sock using soft robotic stretch (SRS) sensors that, upon stretching, cause a change in capacitance (pF) in a linear model [5]. The smart sock can quantify ankle and foot joint complex kinematics both in the sagittal and frontal planes for dorsiflexion, plantar flexion, inversion, and eversion. This smart sock was developed through several iterations using different positioning of the SRS sensors by testing distinct types of non-weight-bearing and weight-bearing individual and dynamic movements, all compared against a three-dimensional (3D) optical motion capture system (MOCAP). The findings and validation of the smart sock have been previously published as the "Closing the Wearable Gap" paper series that includes Parts I to VII [5–11]. With the completion of validation of the smart sock and its reported accuracy to capture ankle and foot joint kinematics, the joint proximal to the ankle in the kinetic chain, the knee joint, was the focus of this current research study [2,5–11]. With the knee joint being a part of the closed kinetic chain of the lower extremity, with predominant bipedal movements requiring various range of motion contributions from the knee joint, and with increased incidence of knee joint injuries, surgeries, and rehabilitation in different populations. such as athletic and geriatric populations, measuring and monitoring knee joint kinematics is highly warranted.

Measuring and monitoring knee joint kinematics is crucial in biomechanical assessments and rehabilitation in clinical and athletic populations. However, researchers and especially clinicians typically use biomechanical tools such as two- or three-dimensional motion capture, electric goniometers, pressure gait mats, force platforms, or instrumented treadmills to assess and monitor overall gait as well as individual joint kinematics to measure a patient's abilities and progress in order to improve the overall function of a movement [12]. These pieces of biomechanical equipment are usually very expensive and predominantly confined within a laboratory or clinical space. With the growing access to and popularity of wearables, these devices are being increasingly used for physical rehabilitation [13–16], monitoring human movement [2], and injury prevention [2]. Such devices can also be used in a variety of rehabilitation scenarios, from neuromuscular or musculoskeletal abnormalities to improving mobility and function. Moreover, such devices can be used as both a diagnostic and a prognostic tool, aiding in the diagnosis of any movement dysfunction and its severity, as well as in monitoring progression with rehabilitation [1]. For example, the additional kinematic and kinetic data from human movement-monitoring wearable devices, such as a smart knee brace, acquired while administering traditional assessments [17] such as a timed up and go (TUG) test, functional gait assessment (FGA), dynamic gait index (DGI), and 6 min walking test (6MT), can better aid in the initial assessment of the neuro-musculoskeletal status for diagnostic purposes as well in periodic assessments over the course of rehabilitation for prognosis [2]. Additionally, depending on the design, wearables and sensors can be less invasive and used outside of a laboratory in the real world with continuous monitoring and actional feedback.

When working with new wearable technology, accurate assessments of the joint movement are of utmost importance, therefore, validation of such devices against the gold standard MOCAP system is critical [18,19]. Previous research investigating the development and use of other types of SRS sensors to measure movement at the knee joint has found success when using multiple sensors [20] and advanced modeling techniques [21]. Specifically, stretch sensors in a brace have been used previously to monitor knee joint movements [20–22]. However, most of these studies use a limited number of participants and do not investigate the use of the technology with a variety of human movement tasks, specifically non-weight bearing and weight bearing, and open and closed kinematic chain movements of the knee joint. Validation will also be needed during various types of dynamic lower extremity movement tasks that require varying degrees of range of motion at the knee joint. Therefore, the purpose of this validation research study was to compare a smart knee brace using SRS sensors against MOCAP in detecting knee joint angle measurements during three dynamic tasks, including: non-weight-bearing knee flexion/extension movements, weight-bearing bodyweight air squats, and walking, utilizing a diverse sample size.

2. Materials and Methods

2.1. Participants

This study was conducted on 16 healthy, college-age individuals (6 males, 10 females; mass: 75.77 ± 13.89 kg; height: 135.59 ± 10.84 cm; age: 21.12 ± 2.79 years) after approval from the Mississippi State University Institutional Review Board (IRB; Protocol # 19-479). The exclusion criteria included individuals with a history of musculoskeletal abnormalities, individuals with an abnormal gait pattern, and participants unable to pass a Physical Activity Readiness Questionnaire (PAR-Q). The rationale for testing a general healthy population of participants beyond the convenient sample was to compare the sensors to the motion capture system without any abnormal knee movement or gait hindrances. A sample size of 10–20 participants has been successfully used previously with significant findings in the Closing the Wearable Gap papers using SRS sensors [5,7–9].

2.2. Instrumentation

The testing included measurements of knee joint kinematics using 12 Bonita™ camera 3D motion capture systems (Vicon™, Oxford, UK) and one StretchSense™ SRS sensor (Auckland, New Zealand), which, when stretched, responds with a change in capacitance (pF) linear to the degree and rate of stretch. This sensor was chosen based on previous research findings from the current research team in the design, development, and validation of this sensor used in a smart sock [5,7–11]. The team has also tested another stretch sensor previously [6], but the current sensor provided a more robust hardware and ease of software solutions. With the concept of progressing from a smart sock to the current validation study for a smart knee brace, the same stretch sensor was selected. Additionally, this sensor was chosen based on preliminary research from the current research team on fatiguing measures, indicating that capacitive-based stretch sensors perform better in terms of linearity and minimal hysteresis in comparison to resistive-based stretch sensors when stretched repeatedly [23]. The SRS sensor was embedded on the anterior portion of a unisex, one-size-fits-all elastic compression knee brace (Sable®, Compression Knee Brace, 88% Nylon 12% Spandex, Item Model Number: SA-PS023, SunValley Brands). The 3D MOCAP data was sampled at 250 Hz and the SRS sensor data were also sampled at 250 Hz. The MotionMonitor™ (Innovative Sports Training, Inc., Chicago, IL, USA) was used with Vicon™ to capture, visualize, and assess the motion capture data. The 3D optical marker-based MOCAP system is considered as a gold standard in human movement monitoring and the markers used in the current study included a marker cluster placed on each body segment to minimize the effects of skin movement artifacts that are an inherent limitation with individual markers placed on the skin [24]. One SRS sensor was placed on the knee in a predetermined placement and orientation configuration (POC) as explained below.

2.3. Sensor Placement and Orientation Configuration

The POC was determined based on the anatomical location of the patella and movement patterns that are possible at the knee joint. Given that the knee joint is a uniaxial modified hinge joint with the predominant degree of freedom being knee flexion/extension movements, and with the SRS sensor responding to a stretch, the sensor was positioned anterior to the knee joint axis over the patella and spanning across the anterior portion of the knee brace (Figure 1). The sensor was located in a position that would cause them to be stretched by the joint motion or task. The individual SRS sensor on the knee brace was then labeled and its position marked and maintained throughout the study.

(**a**) (**b**)

Figure 1. (**a**) Setup of the smart knee brace with embedded soft robotic stretch (SRS) sensor placement and optical motion capture sensors and (**b**) frontal view with smart knee brace being worn.

2.4. Experimental Procedures

After obtaining informed consent, all participants completed one familiarization day consisting of 15 min in which they filled out a PAR-Q to determine exercise and participation readiness. They were then familiarized with the exercise protocol in the Human Performance Laboratory (HPL) of the Center for Advanced Vehicular Systems (CAVS) and anthropometric data were collected. Participants were individually tested on one separate day for the experimental study. First, participants completed a warmup protocol consisting of lunges and gait swings. Then, participants were marked with motion-capture cluster sensors placed on the thigh, shank, and foot of both legs to create a lower extremity model. Participants were then fitted with the smart knee brace on their dominant leg, which is an elastic, compression-sports knee brace with the SRS sensor embedded on the anterior side of the brace. Participants performed three different tasks that included: (A) non-weight-bearing unilateral (dominant) knee flexion/extension movements in a unilateral standing position (non-dominant leg stance), (B) bilateral weight-bearing bodyweight air squats, and (C) walking (Figure 2). One trial of three repetitions was performed for both the knee flexion and extension movement tasks and for the bodyweight air squats, both achieving a 90-degree knee flexion position. Following that, all participants performed six separate gait trials by walking across the HPL (6 m). When the participant concluded all trials, a minimal cooldown protocol with lower extremity stretches was completed, which indicated the end of the experimental procedures for this study.

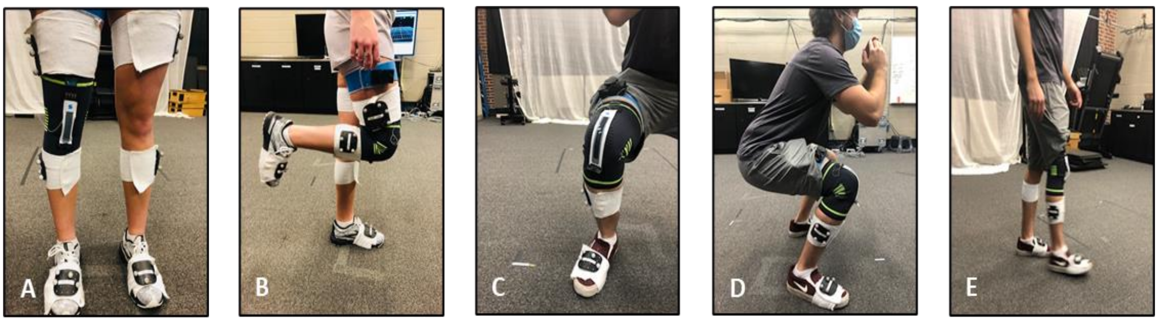

Figure 2. Three tasks assessed during this study. Participant performing (**A**) unilateral non-weight-bearing flexion/extension movements up to full knee extension at anatomical position and then to (**B**) 90-degree flexion; (**C**) Participant performing a bodyweight air squat from frontal view and (**D**) lateral view; (**E**) Participant performing a gait trial.

2.5. Data and Statistical Analysis

Motion capture data were collected at 250 Hz and smoothed with a 30 Hz Butterworth filter. StretchSense™ data were collected at 250 Hz to match the sampling rate of the motion capture system, similar to our previous research methodology [11]. Each trial was saved to a file that was named according to a participant identification number and the movement performed. This naming convention was used to pair the motion capture and SRS data files. When comparing data, the SRS and MotionMonitor™ had corresponding names for the exercises and joint movement (i.e., knee flexion, squat, and walk 1). Cross correlation was utilized to determine the proper data time alignment. The function was applied based on the sensors measuring the movement performed (i.e., knee flexion), as it would be expected that both datasets consistently produce three distinct peaks, with each peak representing knee flexion performed by the participant during each trial. The kinematic data of knee angle (degrees) during these movements from the MotionMonitor™ MOCAP software and the capacitance (pF) change from the SRS sensors were exported for further analyses. An R (statistical computing software) script was used to generate the linear models and calculate adjusted R-squared (R^2), root mean square error (RMSE), and mean absolute error (MAE) values to determine relative and absolute goodness of fit. A detailed description of the linear model comparing motion capture data and stretch sensor data is provided in Parts I-VII of the "Closing the Wearable Gap" paper series from the present research team [5–11].

3. Results

The average R^2, RMSE, and MAE for the three movements (knee flexion, squat, and gait trials) are summarized in Table 1. Individual participant data for the entire study are presented in Appendix A. An example of the preprocessed scaled data is depicted in the figures below for knee flexion/extension movements (Figure 3), bodyweight air squats (Figure 4), and walking gait trials (Figure 5).

Table 1. Average R^2, RMSE, MAE for the three movements/exercises.

Movement/Exercise	Average R^2	Average RMSE (Degrees)	Average MAE (Degrees)
Knee Flexion/Extension	0.799	5.470	4.560
Bodyweight Air Squat	0.957	8.127	6.780
Gait Trials	0.565	9.190	7.530

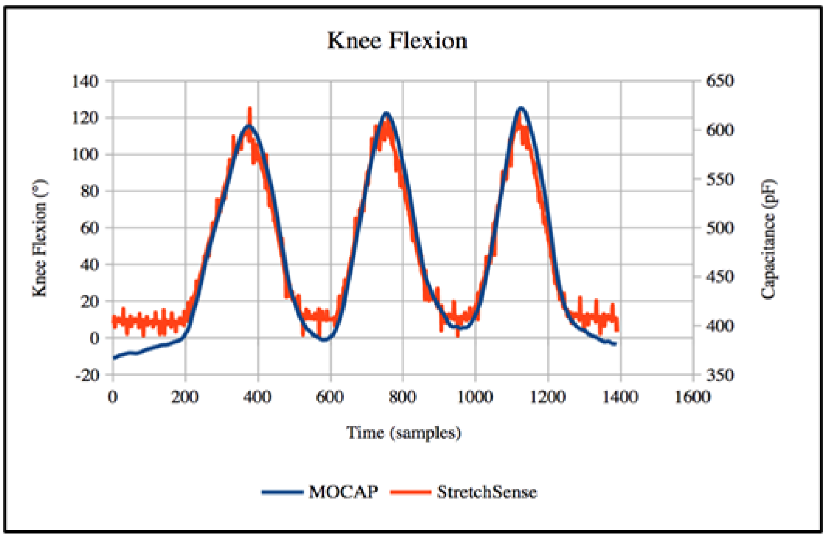

Figure 3. Preprocessed data from SRS sensor and MOCAP for knee flexion.

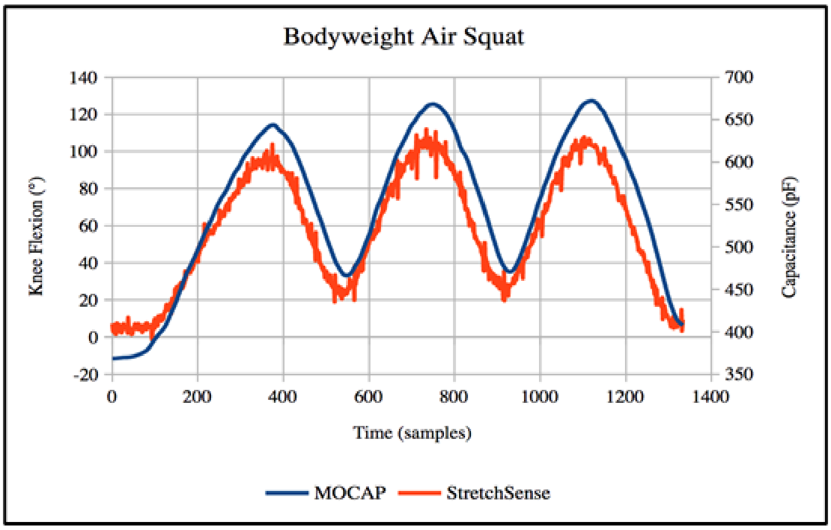

Figure 4. Preprocessed data from SRS sensor and MOCAP for bodyweight air squat.

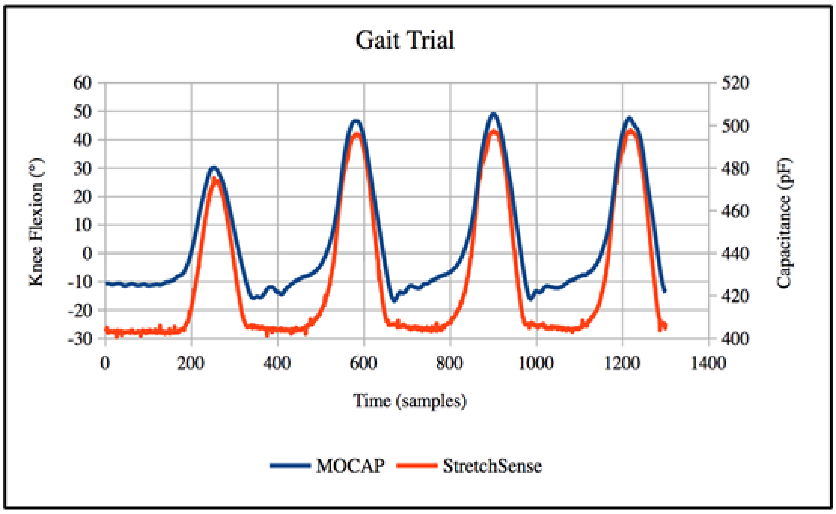

Figure 5. Preprocessed data from SRS sensor and MOCAP for an individual gait trial.

4. Discussion

The purpose of this validation research study was to compare a smart knee brace using SRS sensors against MOCAP in detecting knee joint angle measurements during three different tasks that included: non-weight-bearing knee flexion/extension movements, weight-bearing bodyweight air squats, and walking. While prior validation studies using SRS sensors have already been published [5–11], all of them were limited to the ankle and foot movements. This is the first study to implement the previously developed SRS sensor technology from the smart socks for the knee joint to accurately capture knee joint kinematics. Given the complex nature of using a linear solution to accurately quantify angular human joint movement, and the novel nature of the smart knee brace, three different types of lower extremity movements, that included isolated non-weight-bearing flexion/extension movements, bodyweight air squats, and gait trials, were assessed and compared against a gold standard MOCAP system [19].

Results from the current study indicated that the proposed smart knee brace could serve as a viable product to detect knee joint kinematics based on the derived high adjusted R^2 values and low RMSE and MAE when assessing the goodness of fit model between the motion capture system derived angular kinematics (degrees) and SRS capacitance (pF). A greater goodness of fit and accuracy were evident during unilateral non-weight-bearing flexion/extension movements (R^2 = 0.799) and during bodyweight air squats (R^2 = 0.957), but only moderate goodness of fit and accuracy were evident for gait (R^2 = 0.565). Subsequently, a lower RMSE and MAE in degrees were evident with unilateral non-weight-bearing knee flexion/extension movements and during bodyweight air squats, but gait trials demonstrated the highest RMSE and MAE in degrees. The observed results can be attributed to the position and orientation of the SRS sensors during the assessment, rather than the kinematic differences between the types of movement assessed, such as range of motion achieved, non-weight bearing vs. weight bearing, and open vs. closed kinematic movements. These potential rationales are discussed below.

For knee flexion/extension, results from the study exhibited an average R^2 of 0.799, an average RMSE of 5.470, and average MAE of 4.56 and for the bodyweight air squat trials, R^2 was 0.967, RMSE was 8.127, and MAE was 6.780. A greater goodness of fit and lower errors were interpreted for both these movements. The range of motion targeted in both movements was 90 degrees of knee flexion from a fully extended position. Even with the same range of motion performed in both tasks, the unilateral knee flexion/extension movement was performed as a non-weight-bearing open kinematic chain movement, while the squat was performed as a bilateral weight-bearing closed kinematic chain movement. While both movements demonstrated a greater accuracy, the weight-bearing closed chain squat movement appeared to best monitor knee joint kinematics. Findings from these movements are similar to the previous studies using SRS sensors to quantify the ankle joint range of motion [7,8,10]. The findings demonstrated that the SRS sensors still behaved in a linear fashion and were able to detect the knee joint range of motion during non-weight-bearing and weight-bearing movements.

During the gait trials, R^2 was 0.565, RMSE was 9.190, and MAE was 7.530, which demonstrated a lower goodness of fit and accuracy and higher errors. During a normal gait cycle, the knee joint range of motion requirement is much lower, with the predominant range being 5 degrees to 30 degrees for most of the gait cycle and usually reaching a maximum of 60–65 degrees during the early swing phase in a typically developed individual [25,26]. Even though the range of motion accomplished at the knee joint during normal gait is lower compared to the 90 degrees of flexion achieved in the other two tasks, the position and orientation of the SRS sensor during the dynamic task of gait may be responsible for the observed results rather the range of motion achieved. Past research has reported SRS sensors to accurately measure the dorsiflexion, plantar flexion, inversion, and eversion range of motion at the ankle and foot, both during isolated joint movements and during gait [5,7,8,10], which all have a lower range of motion compared to the knee joint. However, the position and anchoring of the SRS sensor on the knee brace made SRS sensor slack, especially during repetitive dynamic gait cycles, making it less efficient in detecting joint movements. Hence, minor changes in the smart knee brace position during the gait trials, and deviation of the SRS sensor position and orientation from the optimal, could be responsible for the observed results. In future studies, multiple knee braces will be used to obtain a more accurate positioning and anchoring of the SRS sensor on the knee brace and should be the focus of future iterations of the smart knee brace. Based on the findings from the study, the smart knee brace using an SRS sensor can be used as a feasible wearable technology to monitor knee joint kinematics with greater accuracy for non-weight-bearing and weight-bearing flexion/extension movements and with a moderate accuracy for gait.

Finally, while the reported variables of R^2, RMSE, and MAE provide an overall validation of the smart knee brace against the MOCAP system, in order to make a meaningful interpretation of the observed results from the validation study, comparisons should be made with prior similar studies to determine the level of accuracy of the smart knee brace. Hence, comparisons against previous studies from the current research team using the same SRS sensor, as well as comparisons against other researchers' studies, are presented. While higher R^2 values represent greater accuracy of these sensors, measures of error using variables such as RMSE and MAE have been very commonly used in previous literature from the current research team [5,8,10]. These studies reported errors of 4 degrees or less in comparing the SRS sensor to the MOCAP system, indicating high accuracy [5,8,10]. Studies from other research teams using similar stretch sensors have also reported high accuracy with an error of 4 degrees or less [20,21]. Comparing these results to the current initial validation study's findings indicates that the smart knee brace was more accurate during isolated open chain knee joint movements and during closed chain air squat knee joint movements compared to dynamic gait trials. Hence, the current results should be interpreted with caution, and more iterations of design, development, and validation are required for the smart knee brace, specifically for dynamic movements such as walking and running.

4.1. Limitations

A major limitation for this study was the fit of the knee brace, as a one-size-fits-all knee brace was used to accommodate participants with different body anthropometry, given the preliminary research [5–11]. While the one-size-fits-all knee brace was seen as a limitation for the lack of diverse anthropometry testing, the positioning and anchoring of the stretch sensors on the knee brace appeared to be the major issue, due to the slackness of the SRS sensor created during gait trials. The design and structure of the knee brace were also considered a limitation, due to the compression style of the brace, as it did not have enough stability to keep the SRS sensor in place with an optimal baseline stretched position without any slack in the SRS sensor. Hence, sensor position and orientation are of utmost importance to accurately monitor knee joint kinematics, when using SRS sensors and during dynamic movements such as gait.

4.2. Future Research

Future research should focus on validating the smart knee brace using various braces that differ in design, structure, and material to find an optimal knee brace. More specifically, the positioning and anchoring of the SRS sensor on to the knee brace needs modifications for future iterations of the smart knee brace to prevent unwanted slackness in the sensors, especially during dynamic movements such a walking and running. Additionally, the efficacy of such a smart knee brace with varying size, comfort, and fit needs to be researched. Solutions for better embedding of the SRS sensors into the knee brace need to be analyzed as well. While there is potential for the smart knee brace to be used outside the laboratory given the results of the linear models generated from both previous work assessing ankle joint kinematics [5,7,8,10] and the current study's findings, calibration of the SRS sensor for repeatability is still a work in progress for the research team and future work can be done to investigate a calibration procedure that is generalizable to any user without the need for motion capture-based modeling. Additionally, deep learning approaches have been previously suggested for more accurately capturing joint kinematics [5]. Lastly, refinement of the current iteration of the smart knee brace, along with validation of it with a variety of isolated and combined dynamic tasks, such as running, cycling, jumping, etc., is highly warranted.

4.3. Clinical and Research Applications

Various types of wearable technologies have become available to healthcare professionals and to their clients over the past few years [13–16]. These devices have the capability to ease the rehabilitative process without the patient being in an intensive laboratory setting. In other words, wearable technology can provide healthcare professionals with the most appropriate information and feedback in a real-time setting [13–16]. Subsequently, the additional kinematic data of the knee joint provided by a smart knee brace, during traditional assessments such as a TUG, FGA, DGI, and 6MT, as well as over the duration of rehabilitation, can then lead to more efficient assessment, treatment, and monitoring, especially in an "outside of a laboratory" setting. As such, these smart knee braces can be used for any clinical or athletic populations in any setting, such as nursing homes or during sporting events. Based on the current findings, the smart knee brace shows promise to be developed into a wearable technology that can supplement healthcare professionals. However, the current results should be interpreted with caution, specifically for gait trials, which indicated the least accuracy, and more iterations of design, development, and validation are required for the smart knee brace, specifically for dynamic movements such as walking and running.

5. Conclusions

The findings indicate that the smart knee brace demonstrated the greatest R^2 and lowest RMSE and MAE during weight-bearing movements with a maximal range of motion as performed during bodyweight air squats, followed by non-weight-bearing knee maximal flexion/extension and weight-bearing dynamic gait tasks with a minimal range of motion. A greater goodness of fit and accuracy were evident during unilateral non-weight-bearing flexion/extension movements and during bodyweight air squats, but a lower goodness of fit and accuracy were evident during gait trials. Subsequently, a lower RMSE and MAE in degrees were evident with unilateral non-weight-bearing knee flexion/extension movements and during bodyweight air squats, but gait trials demonstrated the highest RMSE and MAE in degrees. Based on the findings from the study, the smart knee brace using SRS sensors can be used as a feasible wearable technology to monitor knee joint kinematics with a greater accuracy for non-weight-bearing and weight-bearing flexion/extension movements and with a moderate accuracy for gait, and needs more design iterations and validations.

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Institutional Review Board Statement: The study was approved by the Institutional Review Board of Mississippi State University (IRB Protocol # 19-479 approved on 19 November 2020).

Informed Consent Statement: Informed consent was obtained from all subjects involved in the study.

Data Availability Statement: Not applicable.

Conflicts of Interest: The authors declare no conflict of interest. The funders had no role in the design of the study; in the collection, analyses, or interpretation of data; in the writing of the manuscript, or in the decision to publish the results.

Appendix A

Table A1. Data for each individual participant. "-" indicates occasions where SRS sensors did not report data. This has been accounted for in averages.

Participant	Movement/Exercise	R^2	RMSE (in Degrees)	MAE (in Degrees)
P001	Knee Flexion/Extension	0.982	5.90	4.91
	Bodyweight Air Squat	0.949	9.04	7.41
	Avg. Gait Trial	0.936	3.99	3.27
P002	Knee Flexion/Extension	0.984	4.78	3.72
	Bodyweight Air Squat	0.972	7.70	6.20
	Avg. Gait Trial	0.861	6.38	4.83
P003	Knee Flexion/Extension	-	-	-
	Bodyweight Air Squat	0.991	3.99	3.28
	Avg. Gait Trial	0.862	6.27	4.97

Table A1. *Cont.*

Participant	Movement/Exercise	R^2	RMSE (in Degrees)	MAE (in Degrees)
P004	Knee Flexion/Extension	0.964	7.66	6.72
	Bodyweight Air Squat	0.988	4.24	3.62
	Avg. Gait Trial	0.916	5.07	4.12
P005	Knee Flexion/Extension	0.992	4.18	3.49
	Bodyweight Air Squat	0.992	3.34	2.70
	Avg. Gait Trial	0.814	6.03	4.07
P006	Knee Flexion/Extension	0.807	3.89	3.40
	Bodyweight Air Squat	0.963	9.57	7.94
	Avg. Gait Trial	0.406	14.13	12.22
P007	Knee Flexion/Extension	0.813	5.38	4.43
	Bodyweight Air Squat	0.954	9.19	7.50
	Avg. Gait Trial	0.316	11.87	9.65
P008	Knee Flexion/Extension	0.540	5.52	4.38
	Bodyweight Air Squat	0.945	8.55	7.00
	Avg. Gait Trial	0.225	12.54	10.81
P009	Knee Flexion/Extension	0.691	4.80	4.09
	Bodyweight Air Squat	0.979	6.38	5.53
	Avg. Gait Trial	0.573	9.33	7.69
P010	Knee Flexion/Extension	0.796	6.53	5.32
	Bodyweight Air Squat	0.976	7.73	6.25
	Avg. Gait Trial	0.393	10.95	9.09
P011	Knee Flexion/Extension	0.759	3.86	3.33
	Bodyweight Air Squat	0.972	7.36	6.15
	Avg. Gait Trial	0.499	8.94	7.37
P012	Knee Flexion/Extension	0.566	5.46	4.25
	Bodyweight Air Squat	0.786	20.16	17.01
	Avg. Gait Trial	0.277	10.02	8.65
P013	Knee Flexion/Extension	0.883	8.59	7.32
	Bodyweight Air Squat	0.953	11.35	9.84
	Avg. Gait Trial	0.471	11.61	9.51
P014	Knee Flexion/Extension	0.421	4.04	3.46
	Bodyweight Air Squat	0.952	9.23	7.54
	Avg. Gait Trial	0.261	10.59	8.51
P015	Knee Flexion/Extension	-	-	-
	Bodyweight Air Squat	0.953	8.84	7.65
	Avg. Gait Trial	0.327	12.11	10.27
P016	Knee Flexion/Extension	0.983	5.99	5.02
	Bodyweight Air Squat	0.988	3.37	2.88
	Avg. Gait Trial	0.763	9.20	6.98

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