Feasibility Study of Real-Time Estimation of Knee Adduction Moment Using Wearable Insole Sensors and Artificial Neural Networks: A Case Report

Benjamin Zhang

Dept. of Physical Therapy and Human Movement Sciences,

Northwestern University Feinberg School of Medicine,

Chicago, IL, USA

Naperville North High School, Naperville, IL, USA

Mentor: Alison H. Chang

Dept. of Physical Therapy and Human Movement Sciences,

Northwestern University Feinberg School of Medicine

Chicago, IL, USA

Abstract

Knee Osteoarthritis (OA) is a chronic condition affecting 645 million adults aged 40 and older worldwide. The external knee adduction moment (KAM), an indicator of medial knee load during walking, is associated with knee pain, disease severity, and structural progression. Real-time monitoring of KAM presents opportunities to retrain gait and potentially alleviate knee symptoms. However, conventional methods for calculating KAM require costly lab setups and equipment, making gait retraining by real-time KAM feedback impractical. Emerging approaches focus on using sensors, such as inertial measurement units (IMUs) and pressure sensors, to estimate KAM. This study aims to evaluate the feasibility of a low-cost method for real-time monitoring of KAM. The positive result will facilitate gait retraining and reduce medial knee load, using wearable pressure-sensing insoles and artificial neural networks.

I. INTRODUCTION

Knee osteoarthritis (OA) is one of the leading health issues in the US, and a chronic condition affecting over 500 million globally [1]. The growing aging population and rising obesity rates are expected to drive a surge in the prevalence of knee OA. Knee OA is the most common form of OA, affecting at least 19% of individuals aged 45 and over and accounting for 80% of all OA cases [2].

Current treatments for knee OA primarily focus on managing pain and preserving function. Clinically, there are no proven disease-modifying agents available to effectively halt or reverse the disease [3]. On the other side, years of research has pointed to gait retraining, particularly through monitoring the external knee adduction moment (KAM), as one of the promising non-pharmacological therapies. As a key biomechanical marker for the medial knee load during walking, KAM has been associated with the progression of knee OA [4,5]. Gait retraining programs that incorporate KAM monitoring and feedback have been shown to successfully reduce symptoms related to knee OA [6].

Unfortunately, these treatment methods are currently not viable for practical, widespread use because current KAM monitoring techniques require expensive and complex laboratory procedures and equipment. The gold standard for conventional calculation of KAM is the inverse dynamics method, which requires the use of force plates and motion capture systems. This setup, combined with the extensive post-processing required for calculating KAM using this approach makes gait retraining using KAM monitoring and feedback difficult to implement outside of a laboratory environment. Therefore, more efficient and cost-effective, practical methods for estimating KAM are essential to enable the broader application of gait retraining strategies.

Several modifications to the inverse dynamic process have been proposed, including simplified calculation methods using lever arms. However, these approaches have been shown to be inaccurate in calculating KAM, often producing significant errors [7]. Other methods have applied machine learning algorithms combined with various sensor-based data collection systems, such as force plates and IMUs [8, 9]. While these methods have shown promise, they remain impractical for daily life in the user's natural living environment, as they rely heavily on controlled laboratory settings and do not allow for continuous KAM monitoring throughout the course of the user's day. Other studies have explored the feasibility of using plantar sensors in combination with neural networks, demonstrating the potential for accurately predicting KAM [10]. However, these studies were limited by sensors that didn't cover all areas of the foot. However, these previous studies suggest the potential of wearable sensor-based systems combined with neural networks for real-time monitoring of KAM.

Among the more practical and cost-effective methods is the use of insoles embedded with sensors. Yi's group developed a sock with embedded pressure sensors [10]. But the stretchable nature of the sock raises concerns about the reliability of its measurements. In contrast, shoe insoles can be custom made for individual users, providing a more stable and reliable measurement platform, making them a potentially superior option compared to the sock-system. We investigated the feasibility of a novel wearable KAM monitoring system, incorporating sensors integrated within shoe insoles and deep learning neural networks. The success of this work could pave the way for translating costly, lab-based investigation into an effective, affordable, user-friendly, and community-based application to benefit individuals with knee OA.

II. METHODS

A. Experimental Procedures

Data from a healthy young male participant with no history of knee injuries or symptoms was reported. The participant was trained to walk in sync with the beats generated by a metronome app at both a fast pace (120 steps/min) and a normal pace (100 steps/min). Following the beats, the participant walked in a straight line across the force plates. To synchronize data collection time between the conventional gait analysis system and the insole, the participant made a pronounced stomp with the initial step at the start of the walking cycle. The participant then continued to walk across the lab, maintaining the rhythm of the beats.

Video recording was used to immediately verify that at least 3 valid steps were recorded for a valid trial. After a few practice trials, the participant successfully completed 6 valid 10-meter walking trials at each pace (normal and fast).

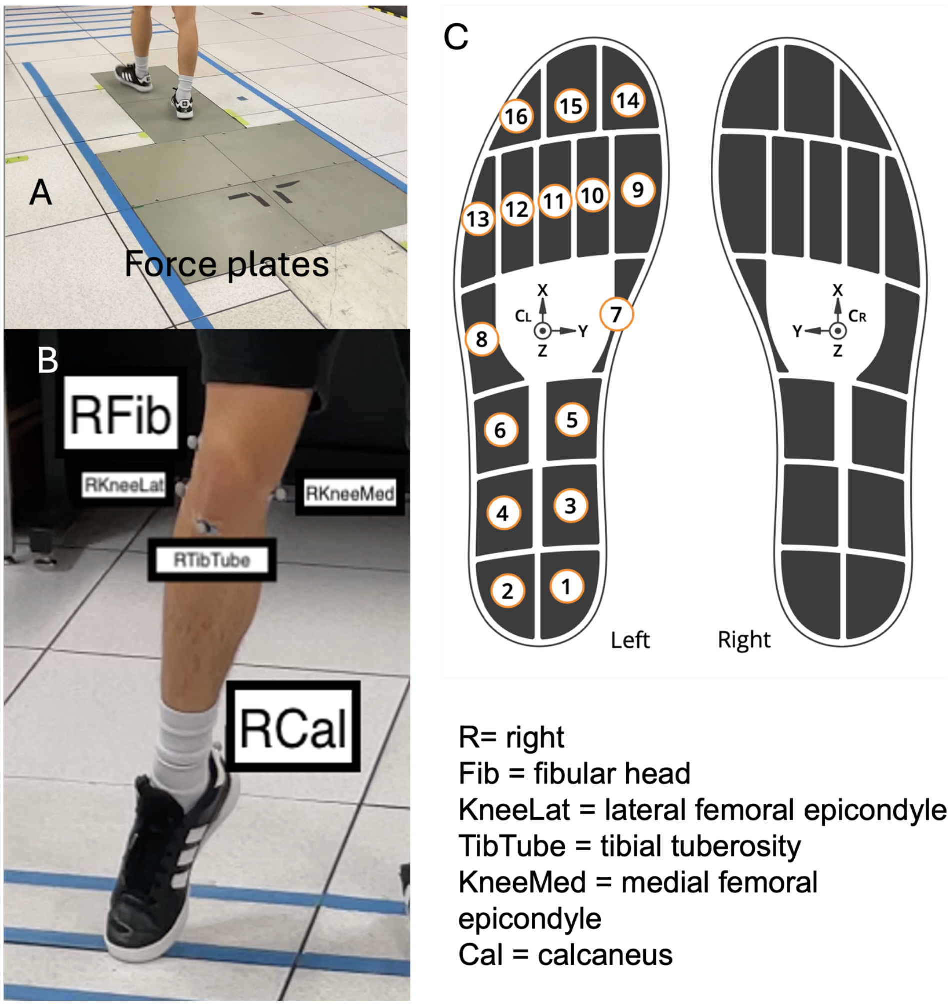

Figure 1. The experiment setup. A, the force plates; B, the marker positions; C, the insoles with pressure sensors (N=1~16) and an IMU.

Conventional gait analysis system includes a three-dimensional motion capture setup consisting of 10 cameras (1,000 frames/s; Oqus, Qualisys, Sweden) and 6 force plates (AMTI, Watertown, MA, USA, see Figure 1A). Five retroreflective markers (14 mm in diameter) were attached to specific bony landmarks, including the medial femoral epicondyle, lateral femoral epicondyle, tibial tuberosity, fibular head, and calcaneus (see Figure 1B). The force plates collected ground reaction force (GRF) data at 10,000 Hz, synchronized with the camera data collection at a sampling rate of 1,000 Hz. Additionally, the participant wore shoes with a pair of insoles (Moticon OpenGo Sensor Insole, Germany) that contained 16 pressure sensors and one IMU (see Figure 1C). The insole data were collected at a frequency of 100 Hz.

B. Knee abduction calculations

Only data from successful trials, where the participant completed the gait cycle without dropping a marker or stepping on multiple plates, were used for analysis. The motion of markers was recorded using Qualisys Track Manager Software.

All data analysis was exclusively performed on the right side. Knee kinematics and kinetics were calculated using Visual 3D (C-Motion, Germantown, MD, USA). The conventional KAM (cKAM) was determined by calculating the moment arm — the perpendicular distance between the center of the knee joint and the line of action of the ground reaction force — and using it to compute the torque about the knee joint, as described by the following equation:

$$\mathrm{cKAM} = \mathrm{My} + \mathrm{F_z} \cdot \mathrm{r_{kneeCOPx}} - \mathrm{F_x} \cdot \mathrm{r_{kneeCOPz}} \quad (1)$$

where My is the moment around the anterior-posterior axis (the y-axis in this context). Fz *and* Fx are the vertical ground reaction force and the ground reaction force in the anterior-posterior direction, respectively. $\mathrm{r_{kneeCOPx}}$ and $\mathrm{r_{kneeCOPz}}$ are the horizontal distance (moment arm) from the center of pressure (COP) to the knee in the x-direction (medial-lateral direction) or the vertical distance (moment arm) from the COP to the knee. The cKAM was then normalized by the participant's weight.

C. KAM prediction using Artificial Neural Networks (ANN) based on insole data

Multiple ANNs were developed using different combinations of sensor data to identify the most effective sensors for plantar pressure monitoring of KAM. For training and testing an ANN model, the Leave-30%-Trial-Out Cross-Validation method was used which involves iteratively selecting 30% random trials as the testing set while using the remaining trials as the training set. Generally, the ANN model was trained using mean absolute error (MAE) as the training metric. The full or partial set of insole data served as the input for the ANN model, and the estimated KAM (eKAM) as the output across time. The conventionally calculated KAM data from each condition was used as the supervised output. The accuracy of the ANN model was assessed by the root mean square error (RMSE) between eKAM and the cKAM.

D. Statistical analysis

ANOVA tests were used for all the statistical analyses. Post-hoc analysis using Bonferroni corrections was used when there were multiple comparisons (i.e., for testing the insole dataset). The significant level was set as $p<0.05$.

III. FINDINGS

Figure 2 displays the total force recorded by the insole during normal-paced (left) and fast-paced (right) walking. In this Figure, the pressure map for normal-paced walking is shown at the corresponding time points, with colors representing the pressure levels.

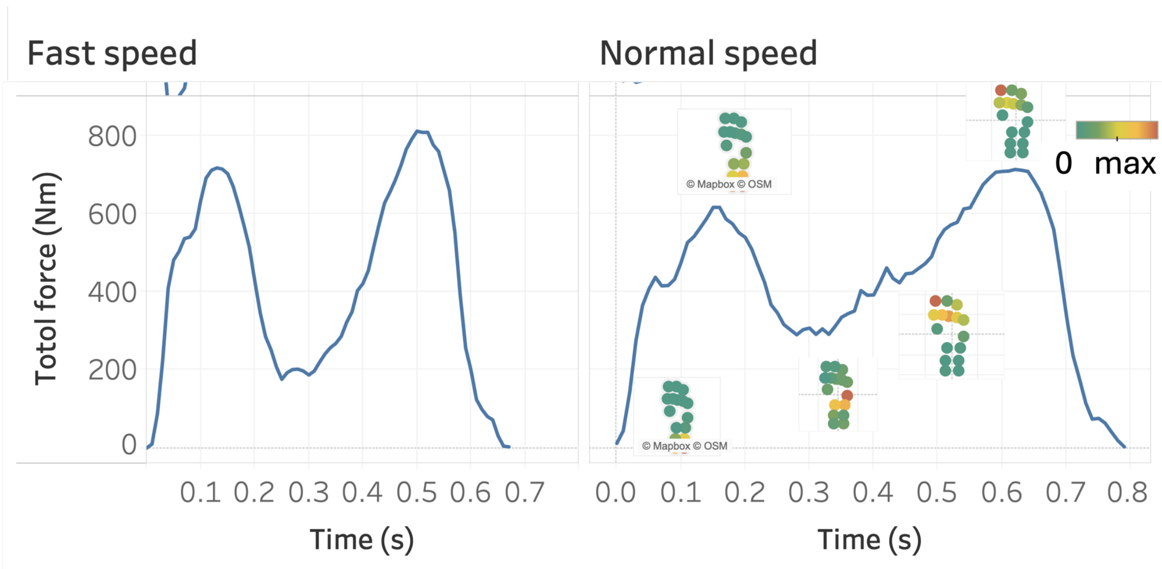

Figure 2. The total force data collected by the insole pressure sensors during one gait with the fast (left) speed and one with the normal (right) speed.

A. The performance of ANN model with increased hidden layers for predicting KAM

The performance of ANN models created using three-hidden layers versus one-hidden layer was compared, using the full insole data (i.e., pressure sensors and IMUs) as inputs. The analysis revealed no significant ($p>0.05$) difference between these 2 models. However, the 1-layer ANN showed a relatively higher RMSE (mean ± std = 0.161±0.010) compared to the 3-layer model (mean ± std = 0.137±0.013). For the remainder of this report, all model-based simulation used the 3-layer ANN.

B. The ANN performance during fast and/or normal walking

By factoring in the walking speed (fast vs. normal pace) as an input to the neural network, we observed a reduction in RMSE for KAM predictions. The ANN showed a significantly lower ($p<0.05$) RMSE for fast walking (mean ± std = 0.107±0.011) compared to normal walking (mean ± std = 0.138±0.016), with both values being lower than the RMSE of the ANN applied across all data (see Figure 3).

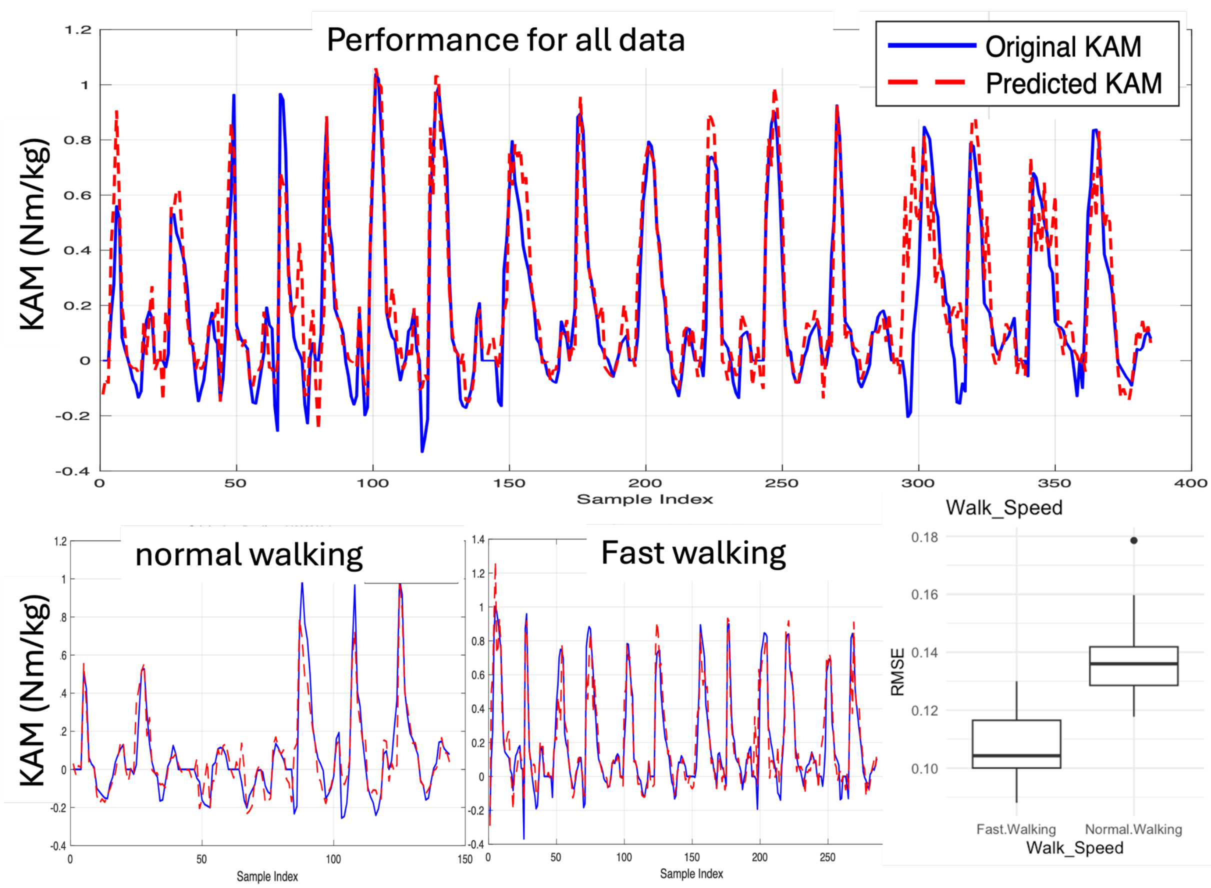

Figure 3. The performance of 3-layer ANN in real-time estimation of the conventional KAM data using the insole pressure sensor data. A, The performance for all data with various speed; B, The performance for normal walking data; and C for the fast-walking data; D, The boxplot of the RMSE for fast vs. normal walking data.

C. The effectiveness of pressure sensors vs. IMUs for predicting KAM

Shown in Figure 4, the performance of the ANN model was significantly impacted by the type of sensors used ($F=31.59$, $p<0.001$). There was no significant difference in RMSE ($p>0.05$) between using input data from pressure sensors only (mean ± std = 0.146±0.008) and the combination of IMU and pressure sensors (mean ± std = 0.136±0.013). However, both significantly outperformed ($p<0.001$) the model using only IMU data (mean ± std = 0.209±0.013).

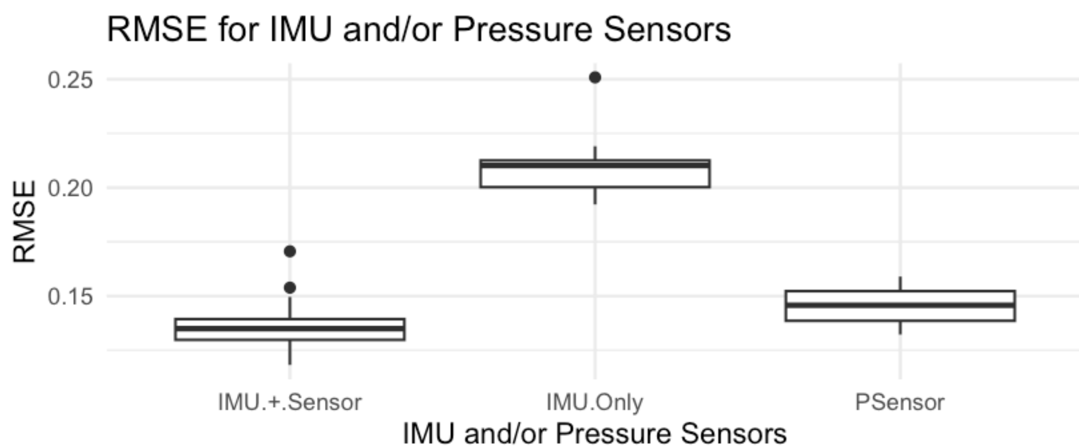

Figure 4. The performance of 3-layer ANN in real-time estimation of the conventional KAM data using A, the insole pressure sensors and IMU; B, IMU only; and C, pressure sensors (PSensor) only.

D. The number and location of pressure sensors needed for accurate KAM estimation

Additional tests were performed to identify which insole anatomical points were most relevant for KAM prediction using plantar sensors. The sensors were numbered as shown in Fig. 1C and models were developed using only select sensors with 3 hidden layers, without distinguishing between walking speeds.

We tested the RMSE for 7 different sensor configurations: (C1), all the 16 pressure sensors, (C2), heel sensors (#1-4) only, (C3), toe sensors (#14-16) only, (C4), forefoot sensors (#10-14) combined, (C5), midfoot sensors (#7-8) only, (C6), toe and heel sensors combined (#1-4 and #14-16), and (C7), forefoot and heel sensors combined (#10-14 and #1-4). Figure 5 presents the RMSE results for the different sensor configurations. The post-hoc analysis showed no significant difference in RMSE between the follow pairs: C6 vs. C7, C2 vs.C4, and C2 vs. C6. All other pairwise comparisons were significant ($p<0.05$). The best performance was achieved using all the 16 pressure sensors. However, when considering a reduction in the number of sensors, the combination of forefoot and heel sensors produced a comparable RMSE (mean ± std = 0.159±0.010).

Similar results were also observed with the combination of toe and heel sensors (mean ± std = 0.162 ± 0.008) and heel sensors alone (mean ± std = 0.172 ± 0.009), highlighting the critical role of heel sensors in KAM prediction

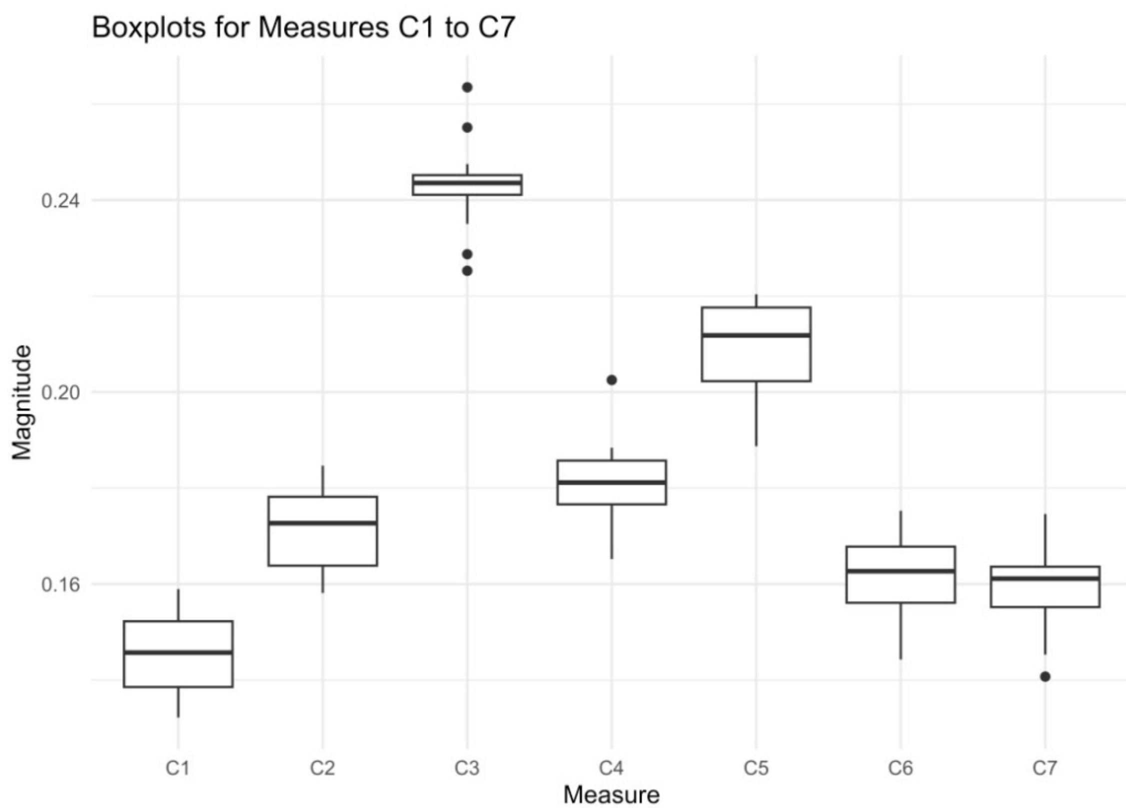

Figure 5. The performance of 3-layer ANN in real-time estimation of the conventional KAM data using various combination of pressure sensors. (C1), all the 16 pressure sensors, (C2), heel sensors (#1-4) only, (C3), toe sensors (#14-16) only, (C4), forefoot sensors (#10-14) combined, (C5), midfoot sensors (#7-8) only, (C6), toe and heel sensors combined (#1-4 and #14-16), and (C7), forefoot and heel sensors combined (#10-14 and #1-4).

IV. DISCUSSION AND FUTURE WORK

Providing real time feedback on KAM while walking holds promise as a treatment strategy to halt progression and prevent the development of knee OA. As one of the first efforts to investigate the feasibility of using cost-effective, wearable insoles for real-time KAM estimation, our results demonstrated that a relatively simple one-hidden layer ANN could achieve an RMSE of approximately 0.16 Nm/kg. Given that the peak KAM in our tested dataset was typically around 0.8 Nm/kg, this corresponds to a relative error of about 20%. The estimation error can be further reduced to 13-17%, depending on the walking speed, when this variable was included in the ANN model. This suggests that walking speed is an important metric to track for accurate real-time KAM estimation when employing this approach.

Our results showed a lower RMSE for fast walking, likely due to the more consistent data, whereas normal walking data exhibited greater variance. As illustrated in Figure 3, despite the reduced estimation accuracy caused by the large variance in KAM during normal walking, the single-layer ANN still performed well in predicting KAM, especially the peak KAM, supporting the strong potential of insole sensors for this application.

The insole we tested is equipped with 16 pressure sensors and one IMU sensor. To explore cost reduction, we evaluated the importance of these sensors in predicting KAM. Our findings indicated that the pressure sensors played a more significant role compared to the IMU. However, IMU data may still be important, considering the relevance of walking speed when predicting KAM. Among all the pressure sensors, those located at the heel area were the most crucial. This result is reasonable, as the peak KAM typically occurs during the early phase of midstance, when pressure from the heel area is at its highest.

The current results are limited by the single case study design and the use of a young, healthy participant. We plan to develop user-specific ANN models, which could enhance the generalizability and relevance of our findings. Future research will focus on testing this user-specific approach by expanding the sample size and including participants with knee OA. This will allow us to assess the robustness of the ANN models across different populations and potentially refine the models.

Ultimately, this work aims to contribute to the development of more personalized and effective interventions for managing and preventing knee osteoarthritis.

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