WORLD SLEEP October 20-25 2023 Rio de Janeiro BRAZIL

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Feasibility of Unobtrusively Measuring Blood Pressure Using Ballistocardiography-based Pulse Transit Times

FINANCIAL RELATIONSHIP DISCLOSURE

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With respect to this CME activity,

[ ] **No**, I (nor my spouse/partner) do not have a relevant financial relationship.

[X] **Yes**, I (and/or my spouse/partner) do have a relevant financial relationship.

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___ Grant/Research Support (Secondary Investigators need not disclose)	
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__X_ Full-time/Part-time Employee	Sleep Number Corporation
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Along with other hemodynamic and autonomous biomarkers, blood pressure changes markedly during sleep

- BP “dips” by ~20% in sleep compared with wakefulness and reaches a minimum between 1.5 and 2.5 hours after sleep onset[1]
- Abnormal BP dipping patterns are associated with cardiovascular risks[2]
  - BP dipping > 20% is associated with increased risk for ischemic stroke[2]
  - BP dipping < 10% is associated with increased risk for myocardial infarction[2]

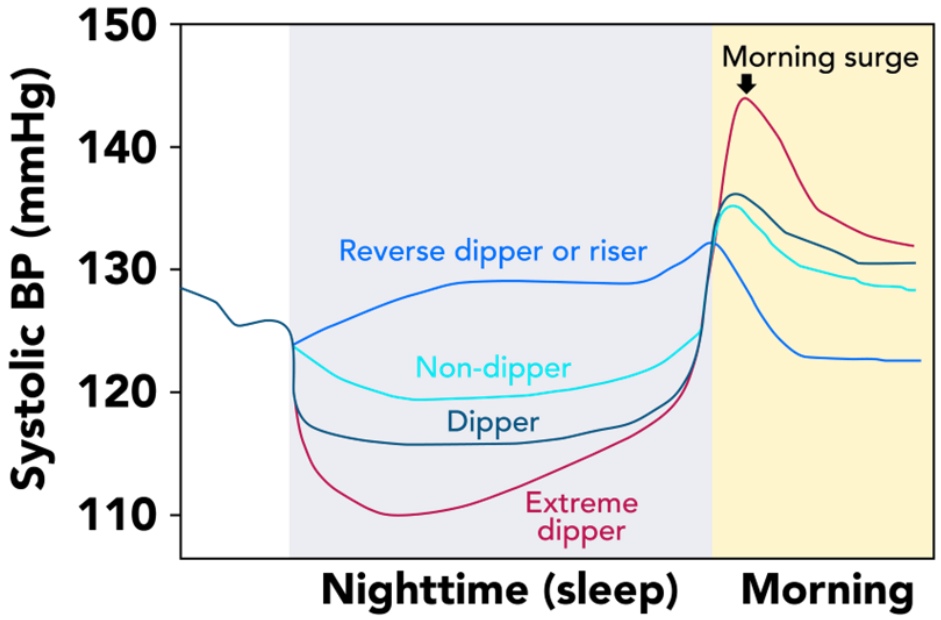


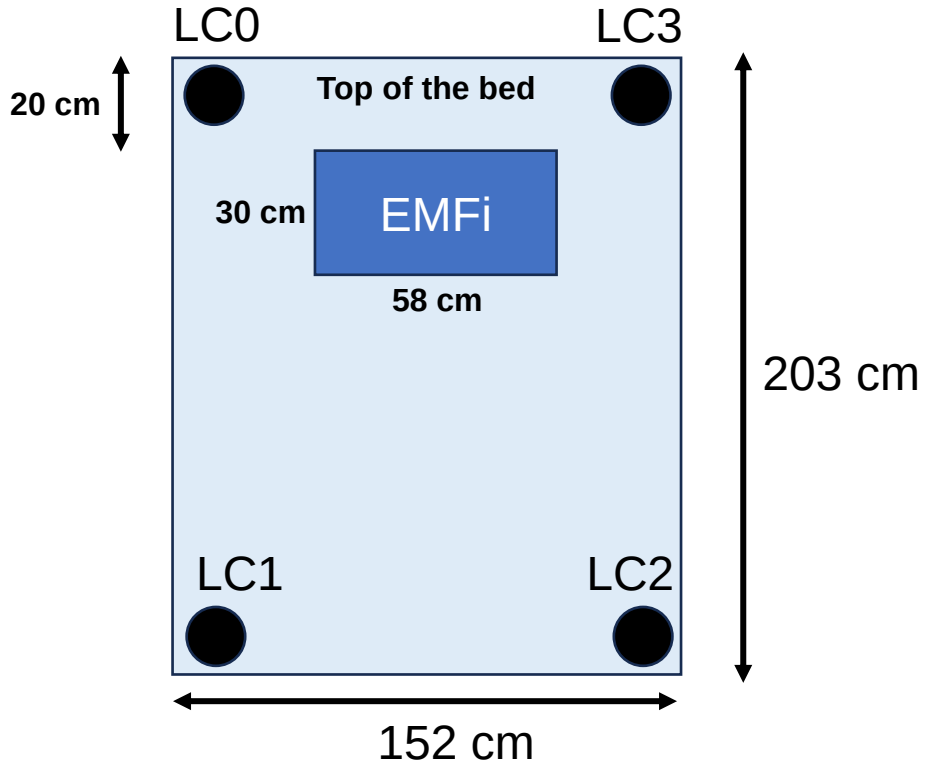
Figure was adapted from Cho MC, *Korean Circ J.* 2019

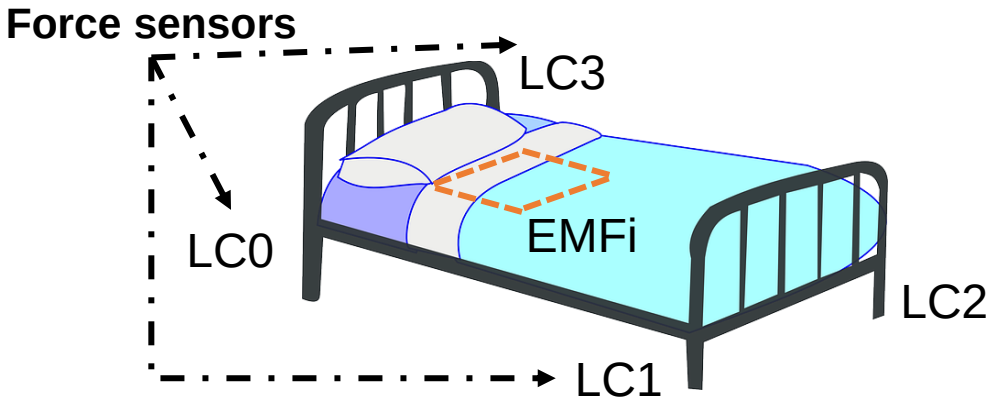
BP, blood pressure.

1. Snyder F et al. *J Appl Physiol*. 1964;19:417–422; 2. Cho MC. *Korean Circ. J*. 2019;49:9:818–828.

The aim of this study was to test the feasibility of unobtrusively estimating BP using force-sensor data from a smart bed

- Publicly available data were used, which included:
  - Force-sensor BCG (from the LCs),
  - Electromechanical BCG (from the EMFi films),
  - ECG,
  - Continuous blood pressure[1,2]
- The signals were synchronously acquired from a smart bed equipped with the following:
  - Four LCs and EMFi electromechanical films
  - A Finapres® Finometer PRO was used to continuously estimate BP from the finger arterial pressure waveform





BCG, ballistocardiography; BP, blood pressure; ECG, electrocardiography; LC, load cell.
1. Carlson C et al. *Sensors (Switzerland)*. 2021;21(1)156:1–13; 2. Carlson C et al. *IEEE Dataport*. 2020.

The publicly available data from 40 participants were used

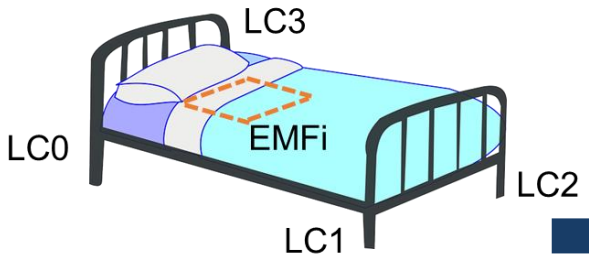
All data utilized were publicly available from a single dataset.[1,2]

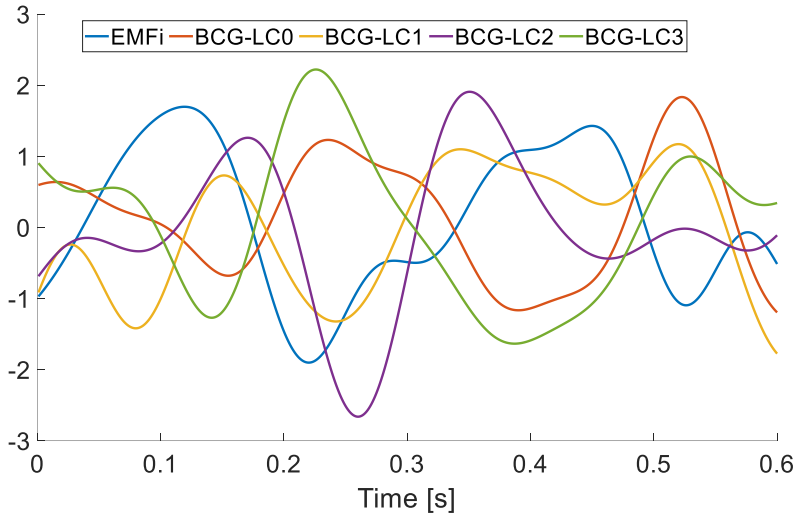
	Participants (N = 40)
Male, n (%) Female, n (%)	17 (42.5) 23 (57.5)
Age, years, mean ± SD	33.9 ± 14.4
BMI, kg/m^2, mean ± SD	26.0 ± 5.6
Recording duration, seconds, mean ± SD	418.2 ± 26.5

BMI, body mass index; SD, standard deviation.

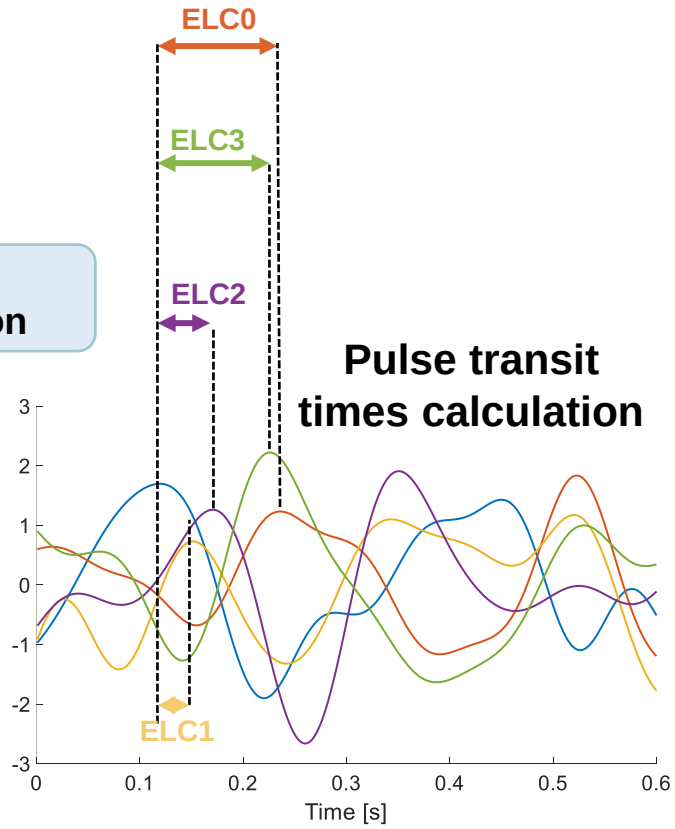
1. Carlson C et al. *Sensors (Switzerland)*. 2021;21(1)156:1–13; 2. Carlson C et al. *IEEE Dataport*. 2020.

Data processing





Peak detection



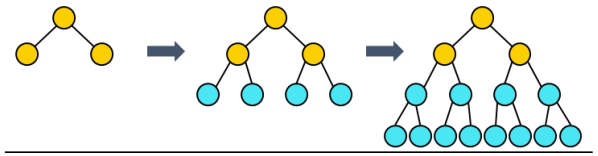
Pulse transit times calculation

1. IBI (interbeat interval) duration
2. ELC0
3. ELC1
4. ELC2
5. ELC2

Feature vector per IBI

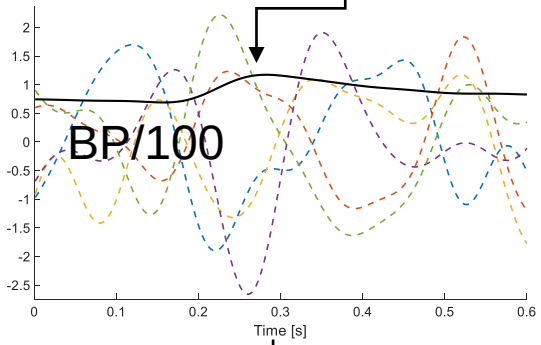
ELCj: difference in milliseconds between peaks in BCG-LCj (where j = 0–3) and EMFi BCG

Boosted decision tree regression model



SBP prediction

Systolic BP (SBP) Local maximum



Accuracy calculation

BCG, ballistocardiography; BP, blood pressure; ELCj, estimated pulse transit time associated with load cell j, where j = 0–3; IBI, interbeat interval; LC, load cell; s, second; SBP, systolic blood pressure.

Two model approaches were considered to predict SBP

1. Participant-independent model

- Trained with 70% of the data
- Performance evaluated using 30% of the data
- Average and SD were calculated across 3 runs

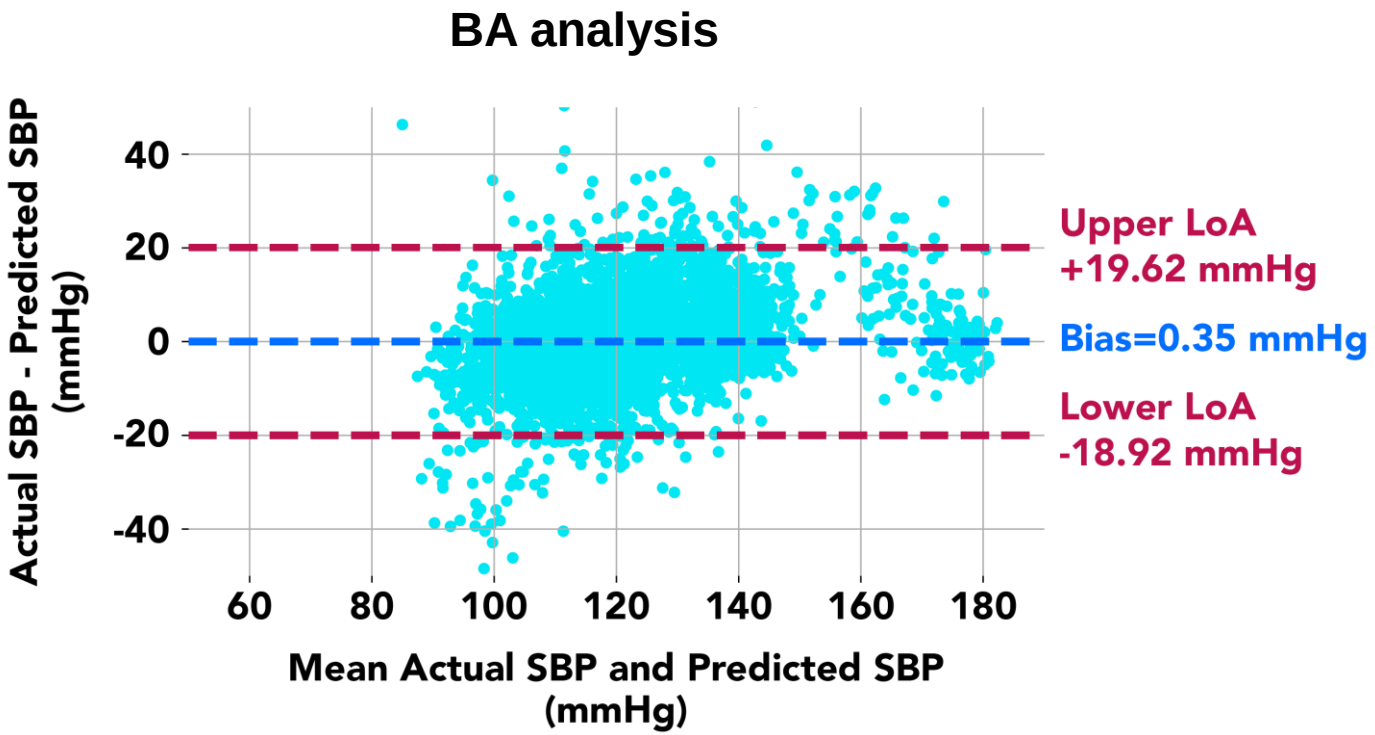
2. Participant-dependent model

- **Generic model**: trained with the data from participants other than the target participant
- Fine tuning of the generic model using a fraction of data from the target participant
- Performance evaluation on the remaining data from the target participant

SBP, systolic blood pressure; SD, standard deviation.

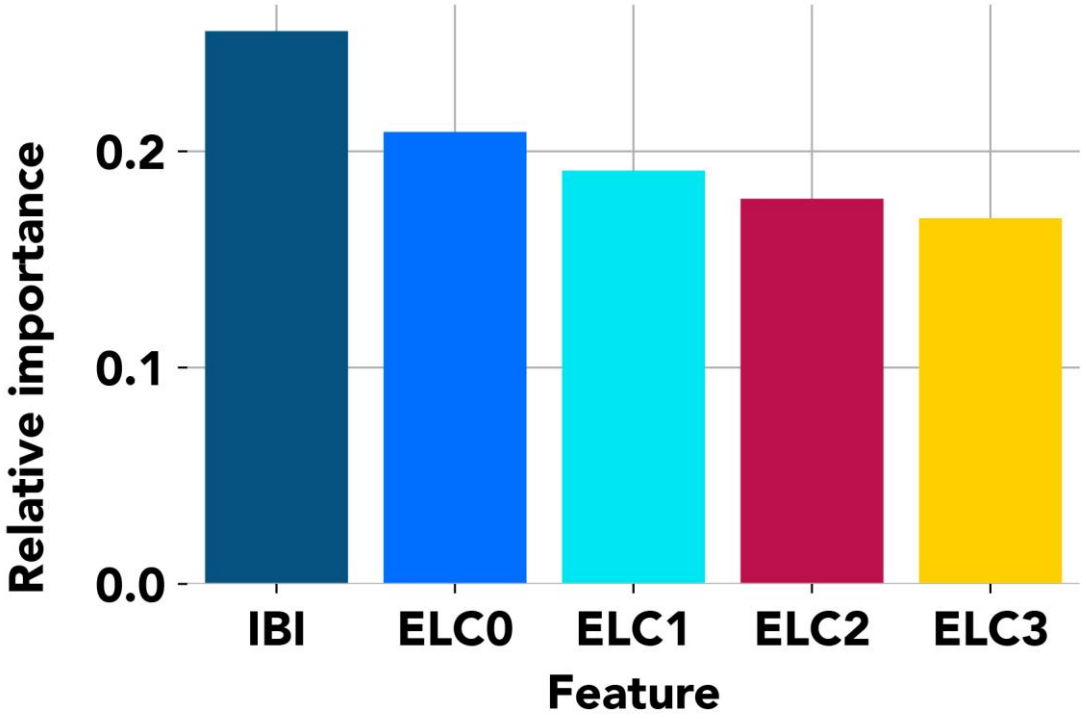
Participant-independent model showed moderate ability to predict SBP

	Instantaneous SBP Mean ± SD	Mean SBP ± SD
Pearson correlation coefficient	0.79 ± 0.04	0.79 ± 0.008
Coefficient of determination R^2	0.63 ± 0.06	0.62 ± 0.007
BA: bias (mmHg)	0.35 ± 0.13	0.32 ± 0.01
BA: lower limit (mmHg)	−18.9 ± 2.37	−8.79 ± 2.23
BA: upper limit (mmHg)	19.6 ± 2.36	9.45 ± 2.22



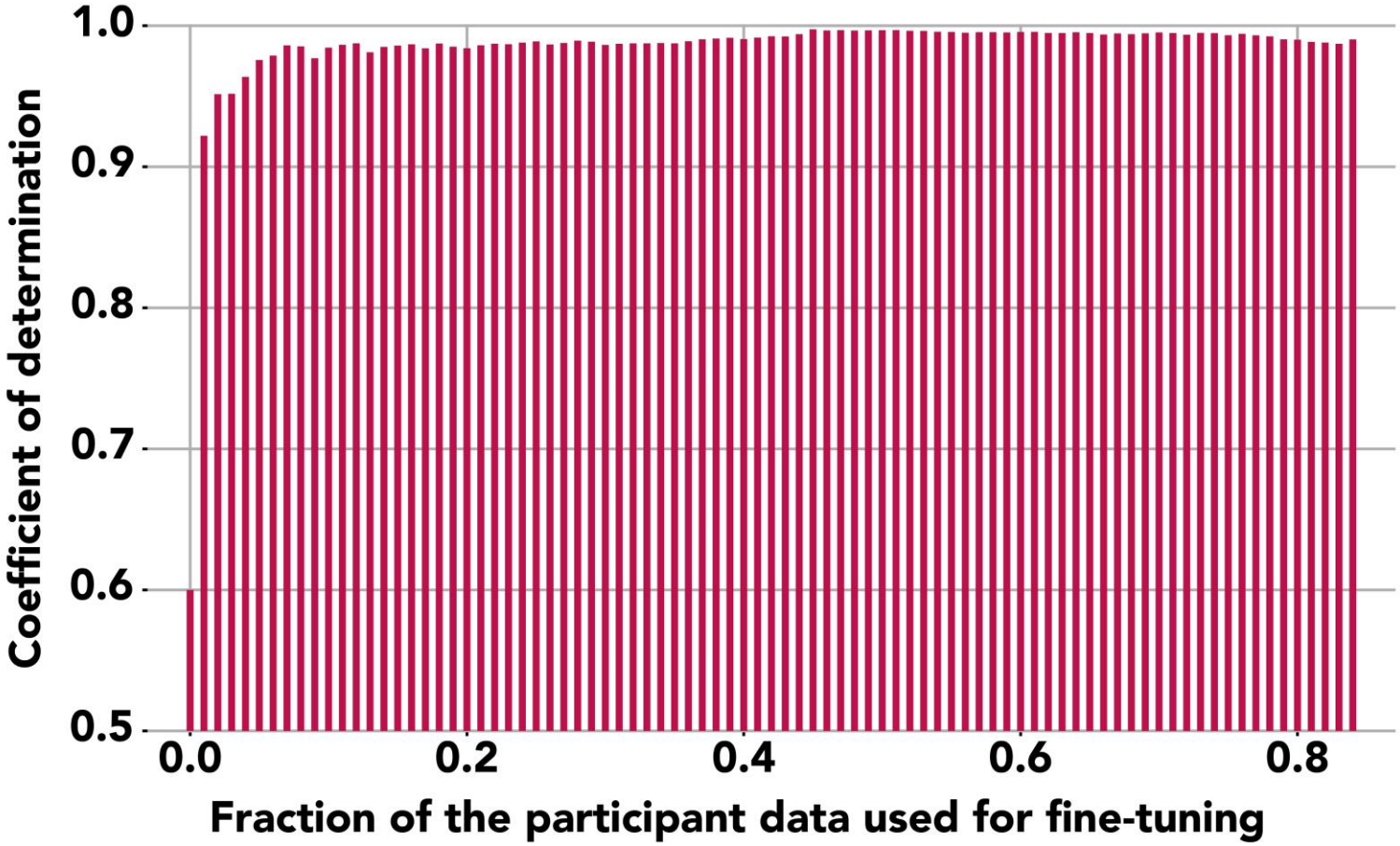
BA, Bland-Altman; LoA, limit of agreement; SBP, systolic blood pressure; SD, standard deviation.

IBI was the most important feature for predicting SBP in the subject-independent model



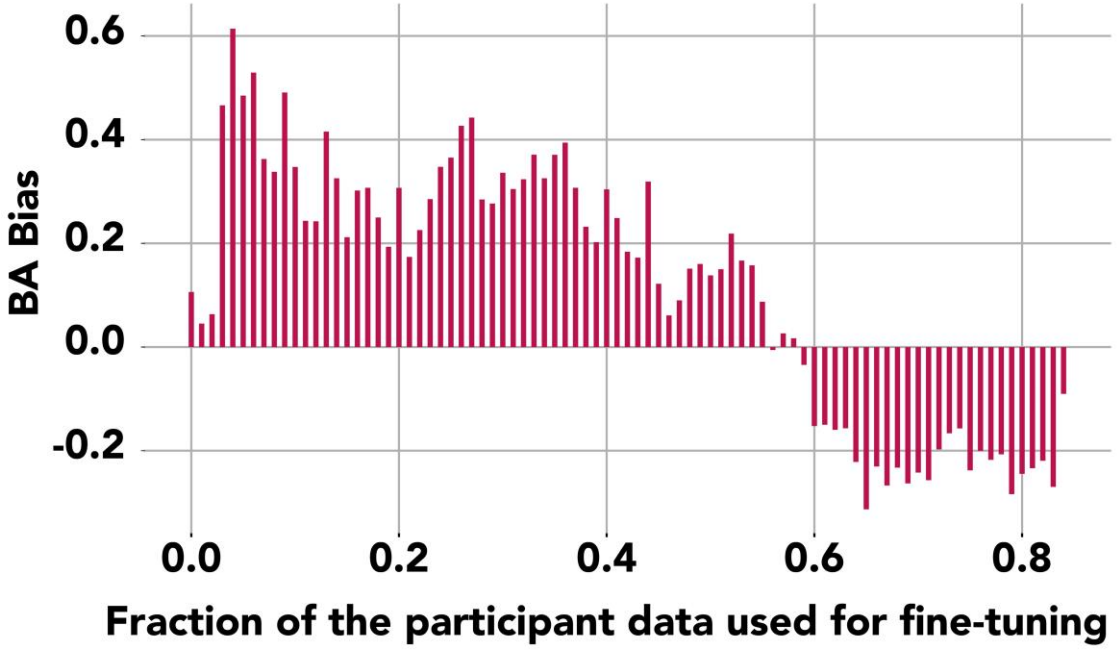
ELCj, estimated load cell PTT associated with load cell j, where j = 0–3; IBI, interbeat interval; PTT, pulse transit time; SBP, systolic blood pressure.

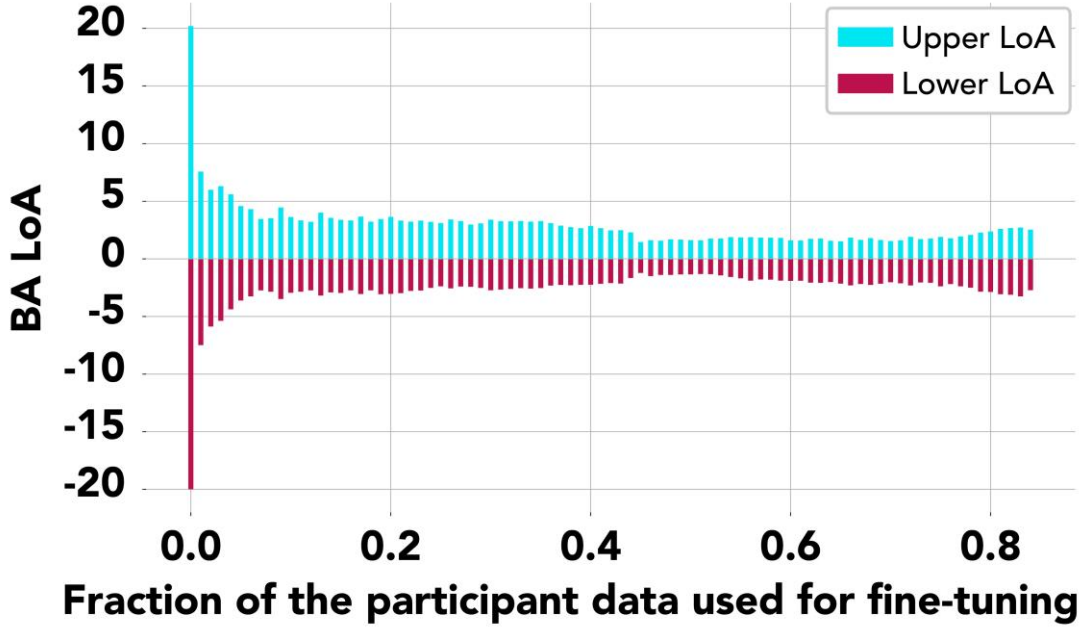
The participant-dependent model more accurately predicted SBP using fine-tuning data



SBP, systolic blood pressure.

The amount of fine-tuning data can be optimized to minimize bias and the BA limits of agreement





BA, Bland-Altman; LoA, limit of agreement.

Conclusions

- **Participant independent model**:
  - The boosted decision tree estimated SBP with mean R^2 of 0.63
  - The BA limits of agreement were in the −10 mmHg to +10 mmHg range. While these are large, they may still enable detection of lack, reduced, or excessive BP dipping
- **Participant dependent model**:
  - Fine-tuning the model with the addition of participant data, similar to transfer learning,[1] substantially increased accuracy

Our findings support the use of force sensors in a smart bed to unobtrusively estimate SBP during sleep. Our algorithm can detect SBP changes that may be beneficial to assessment of cardiac risk

BA, Bland-Altman; BP, blood pressure; SBP, systolic blood pressure.

1. Panigrahi S et al. *Smart Innov Syst Technol*. 2021;194(10):781–789.

Disclosures and acknowledgments

- The author would like to acknowledge the initiative of Carlson et al.[1,2] for making their data publicly available, which allowed the performance this study, and Shawn Barr from Sleep Number Labs for insightful guidance on the manuscript for which this presentation is based
- Medical writing support was provided by George Pellegrino, MD, PhD, of Oxford PharmaGenesis, Inc, Newtown, PA, USA, and was funded by Sleep Number Corporation

- Gary Garcia-Molina is an employee of Sleep Number Corporation
- Patent application on this concept US20230190199A1 “Bed having features to passively monitor blood pressure” (link)

1. Carlson C et al. *Sensors (Switzerland)*. 2021;21(1)156:1–13; 2. Carlson C et al. *IEEE Dataport*. 2020.