# Embodrink: Embodied MR for Physiology-Informed Beverage Recommendation


Prasanth Sasikumar
im_psk@nus.edu.sg
Augmented Human Lab, National University of Singapore
Singapore, Singapore

Takahiro Masuda
takahiro.masuda@asahi-qi.co.jp
Asahi Quality & Innovations, Ltd.
Ibaraki, Japan

Soundarya Ramesh
soundarya@ahlab.org
Augmented Human Lab, National University of Singapore
Singapore, Singapore

Hyung Woon Lee
leehw@ahlab.org
Augmented Human Lab, National University of Singapore
Singapore, Singapore

Sankha Cooray
sankha@ahlab.org
Augmented Human Lab, National University of Singapore
Singapore, Singapore

Suranga Nanayakkara
suranga@ahlab.org
Augmented Human Lab, National University of Singapore
Singapore, Singapore


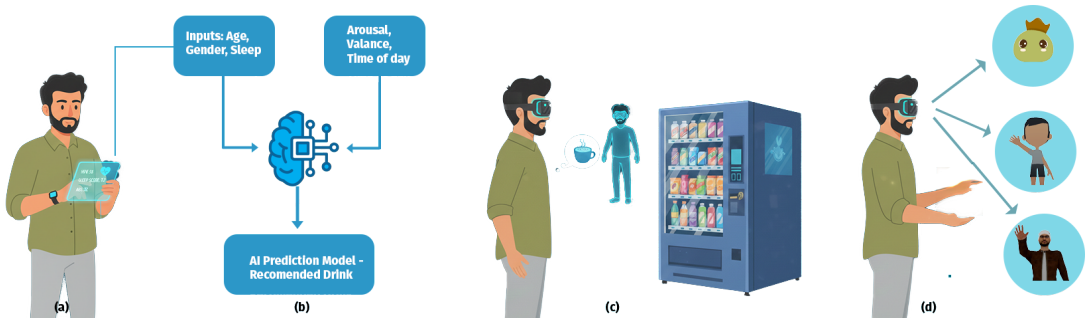


**Figure 1: (a) User data collection via tablet input, self-reported sleep and mood, and physiological sensing. (b) A contextual model generates a drink suggestion from these inputs. (c) The user interacts with an embodied agent with a virtual vending machine. (d) Multiple visualizations present the recommendation**


## Abstract

Wearable devices increasingly capture physiological signals related to users' affective and cognitive states, yet these signals are commonly presented through numerical dashboards that are difficult to interpret and act upon in everyday contexts. We present *Embodrink*, a Mixed Reality (MR) research framework for communicating physiology-informed wellbeing recommendations through embodied representations. Embodrink integrates smartwatch-derived signals with brief self-reports and contextual cues to generate a single beverage recommendation, then holds this recommendation constant while varying how it is presented: an abstract visualization, a generic embodied agent, and a personalized "future self" avatar. Through a walk-up-and-use MR experience, attendees can directly compare how embodiment shapes trust, comfort, and interpretability when engaging with identical wellbeing guidance.




*Conference'17, Washington, DC, USA*



ACM ISBN 978-x-xxxx-xxxx-x/YYYY/MM
https://doi.org/10.1145/nnnnnnn.nnnnnnn



## CCS Concepts

• **Human-centered computing** → **Interaction design**; **Human computer interaction (HCI)**;

**ACM Reference Format:**
Prasanth Sasikumar, Takahiro Masuda, Soundarya Ramesh, Hyung Woon Lee, Sankha Cooray, and Suranga Nanayakkara. 2026. Embodrink: Embodied MR for Physiology-Informed Beverage Recommendation. In . ACM, New York, NY, USA, 3 pages. https://doi.org/10.1145/nnnnnnn.nnnnnnn


## 1 Introduction

Personalized recommender systems increasingly shape everyday food and beverage choices [1, 2, 5]. While they model preferences using feedback, behavior, and context, they rarely incorporate physiological signals reflecting momentary affective states (e.g., stress or fatigue). Wearables continuously capture such signals, yet outputs are typically presented as raw metrics that are difficult to interpret or translate into action [7, 8], creating a gap between sensing and decision-making.

We present *Embodrink*, an interactive MR framework that integrates physiological data, self-reported sleep and mood, and context to generate beverage suggestions. The underlying recommendation is held constant across three modalities - abstract visualization, generic embodied agent, and personalized avatar - enabling

**Figure 2: Virtual vending machine with wearable sensing.**

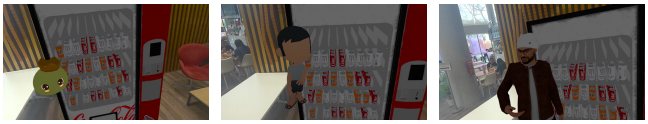

**Figure 3: Embodiment conditions in EmoDrink: abstract visualization (left), generic humanoid embodiment (center), and personalized avatar embodiment (right).**

comparison of how embodiment shapes interpretation of identical wellbeing advice within a virtual vending-machine scenario.

## 2 Background, Related Work, & Design Rationale

Embodrink draws on personal informatics and embodied interaction research. Users often struggle to translate fragmented physiological metrics into actionable understanding in everyday contexts [6, 8], while embodiment influences engagement, trust, and perceived credibility [3, 4]. We treat embodiment as a primary design variable for communicating identical physiology-informed recommendations. The system applies a coarse arousal–valence model derived from physiological and contextual inputs (e.g., HRV, sleep, time-of-day). This low-resolution inference avoids false precision, accommodates ambiguity, and frames outputs as reflective rather than diagnostic. A virtual vending machine provides a familiar, low-stakes context for presenting recommendations, with a curated drink set (e.g., calming, hydrating, energizing) enabling clear cross-modality comparison.

## 3 System Implementation

Embodrink is implemented in Unity on a Meta Quest 3 with hand tracking enabled. The system comprises: (1) sensing and inference, (2) a recommendation backend, and (3) an embodied MR visualization layer.

*Sensing, Inference, and Recommendation.* Physiological signals are captured using a Garmin Venu 3S smartwatch and streamed via a companion application to a backend service, where signals are time-stamped and combined with brief self-reports (mood, sleep quality, energy) and contextual cues. A lightweight inference module estimates coarse affect (arousal/valence), and a recommendation engine produces a single beverage recommendation and structured rationale fields used for explanation.[1] The recommendation is held

[1]For details of the recommendation engine and feature design, refer to [9].

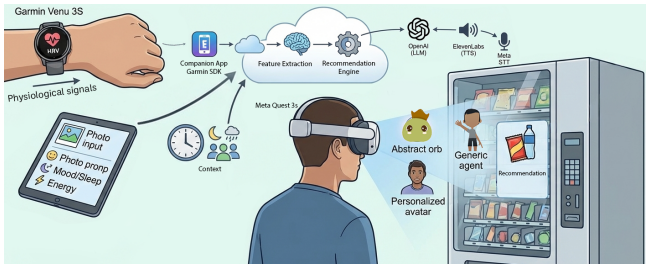


**Figure 4: Overview of the system.**

constant across all visualization modalities to isolate the effect of embodiment.

*Dialogue and MR Rendering.* The system generates natural-language explanations from the fixed recommendation and rationale fields using an LLM, and delivers them through speech (text-to-speech) with optional lightweight voice input (speech-to-text) for user acknowledgements and questions. The MR scene is rendered in passthrough using the Meta Passthrough API so the vending machine and embodied representations appear spatially situated in the user's physical environment.

## 4 The Interactivity Experience

The demonstration provides a 5–7 minute walk-up experience. During onboarding (1–2 min), participants wear a smartwatch, report mood, sleep, and energy, and capture a tablet photo to generate a personalized avatar, producing a *single* recommendation that remains fixed. In the guided comparison phase (2–3 min), users enter MR and encounter the same recommendation through three modalities - an abstract visualization (data orb), a generic embodied agent, and a personalized avatar - with randomized order and system-controlled transitions. In reflection (1–2 min), participants may revisit modalities and access explanation details (e.g., rationale or ingredients) via voice or gesture. Finally, they complete a brief questionnaire assessing trust, clarity, comfort, and actionability (Appendix A), provide preference rankings and optional feedback, while the system logs interaction traces (e.g., order, duration, queries) for within-subject analysis.

## 5 Conclusion

Embodrink explores how physiology-informed wellbeing recommendations can be communicated through embodied mixed reality interfaces, emphasizing *how* recommendations are presented rather than *how accurately* affect is inferred. By holding the underlying recommendation constant and varying only embodiment, the system foregrounds representation as a core interaction design variable in affect-aware systems. As a Demo experience, Embodrink enables direct, within-subject comparison between an abstract visualization, a generic embodied agent, and a personalized avatar in a familiar, low-stakes vending-machine scenario. More broadly, Embodrink functions as a modular research probe for studying embodiment, interpretability, and trust in future wearable and AR systems.

## References


[1] Gediminas Adomavicius and Alexander Tuzhilin. 2005. Toward the Next Generation of Recommender Systems: A Survey of the State-of-the-Art and Possible Extensions. *IEEE Transactions on Knowledge and Data Engineering* 17, 6 (2005), 734–749. doi:10.1109/TKDE.2005.99

[2] Gediminas Adomavicius and Alexander Tuzhilin. 2015. Context-aware recommender systems. In *Recommender Systems Handbook* (2 ed.). Springer, 191–226. doi:10.1007/978-1-4899-7637-6_6

[3] Kirsten Bergmann and Stefan Kopp. 2015. The impact of embodiment on user interaction with conversational agents. *AI Magazine* 36, 4 (2015), 63–74.

[4] Justine Cassell. 2000. Embodied conversational agents. In *MIT Press.*

[5] David Elsweiler, Hanna Hauptmann, and Christoph Trattner. 2022. *Food Recommender Systems* (3 ed.). Springer, 871–925. doi:10.1007/978-1-0716-2197-4_23

[6] Daniel A. Epstein, An Ping, James Fogarty, and Sean A. Munson. 2015. A Lived Informatics Model of Personal Informatics. In *Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing (UbiComp '15).* 731–742. doi:10.1145/2750858.2804250

[7] Ravi Karkar, James Fogarty, Julie A. Kientz, Sean A. Munson, Roger Vilardaga, and Jasmine Zia. 2015. Opportunities and Challenges for Self-Experimentation in Self-Tracking. In *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and the 2015 ACM International Symposium on Wearable Computers (UbiComp/ISWC '15 Adjunct).* 991–996. doi:10.1145/2800835.2800949

[8] Ian Li, Anind K. Dey, and Jodi Forlizzi. 2010. A Stage-Based Model of Personal Informatics Systems. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems (CHI '10).* ACM, 557–566. doi:10.1145/1753326.1753409

[9] Soundarya Ramesh, Takahiro Masuda, Lee Hyung Woon, Yongquan Hu, and Suranga Chandima Nanayakkara. [n. d.]. Don't Sleep on Sleep Data: Influence of Sleep Physiological Signals on Stress Detection. In *NeurIPS 2025 Workshop on Learning from Time Series for Health.*


## A Post-Experience Questionnaire

Participants completed a brief post-experience questionnaire immediately after the EmoDrink interactivity. Unless otherwise noted, all items were rated on a 7-point Likert scale (1 = Strongly disagree, 7 = Strongly agree).

### A.1 Per-Modality Ratings

The following items were completed separately for each of the three embodiment modalities: *Abstract Visualization*, *Generic Embodied Agent*, and *Personalized Avatar*.

(1) **Trust:** "I trust the recommendation presented in this form."
(2) **Clarity:** "I understood why this recommendation was suggested."
(3) **Comfort:** "This representation felt comfortable rather than intrusive."
(4) **Actionability:** "This representation helped me decide what to do."

### A.2 Overall Comparison

(5) **Preference Ranking:** "Rank the three representations by overall preference."
(1 = Most preferred, 3 = Least preferred)
(6) **Consistency Check:** "The recommendation remained the same across all representations."
(Yes / No / Not sure)

### A.3 Privacy and Reflection

(7) **Privacy Concern:** "The personalized avatar felt privacy-invasive."
(8) **Open-Ended:** "Briefly explain why you preferred one representation over the others."

In addition to self-report responses, the system automatically logged interaction metrics including time spent with each modality, order of modality exposure, number of voice queries, and modality revisits.