Using Wearables and IoT Data to Understand Buildings and Cities Better

Assoc. Prof. Clayton Miller





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building and urban data science

BUDS Lab is a scientific research group that leverages data sources from the built and urban environments to improve the energy efficiency and conservation, comfort, safety and satisfaction of humans.



















http://budslab.org/

The Age-Old Question in the Built Environment

What do occupants want?

How do we understand what makes them feel satisfied with their environment?

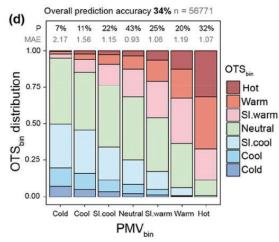




Let's start with Thermal Comfort

The Traditional PMV-PPD Model is only accurate 1 out of 3 times

- Observed Thermal Sensation from ASHRAE Thermal Comfort Database II (56,771 sample) versus the Predicted Mean Vote (PMV) model
- Accuracy on the seven-point thermal sensation scale is only 34%





Cheung, T., Schiavon, S., Parkinson, T., Li, P., & Brager, G. (2019). Analysis of the accuracy on PMV – PPD model using the ASHRAE Global Thermal Comfort Database II. *Building and Environment*, *153*, 205–217. https://doi.org/10.1016/j.buildenv.2019.01.055

Maybe factors like gender or age are the issue?

"There is no clear and consistent conclusions as to the significance and size of inter-group differences in thermal comfort (between females and males, or the young and the old)."

Gender-related Differences

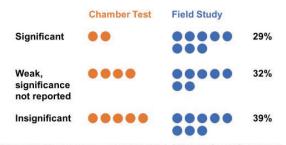


Fig. 1. Literature summary on gender-related differences in comfort temperature.

Age-related Differences



Fig. 4. Summary on age-related differences in comfort temperature.

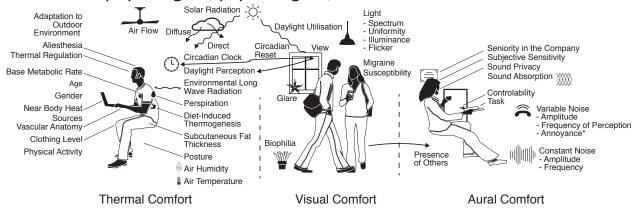


Wang, Z., de Dear, R., Luo, M., Lin, B., He, Y., Ghahramani, A., & Zhu, Y. (2018). Individual difference in thermal comfort: A literature review. *Building and Environment*, *138*, 181–193. https://doi.org/10.1016/j.buildenv.2018.04.040

Must be more factors to measure, right?

Looking at thermal, visual, and aural comfort – there are dozens of factors!

Can we create effective ways to measure or infer all these environment, physiological, psychological, and behavioral attributes?





Jayathissa, P., Quintana, M., Abdelrahman, M., & Miller, C. (2020). Humans-as-a-Sensor for Buildings—Intensive Longitudinal Indoor Comfort Models. *Buildings*, 10(10), 174. https://doi.org/10.3390/buildings10100174

Digitization of human perception in a scalable way!

Social media companies capture human perception using innovation in the way they collect information:



They create digital platforms that provide value to users



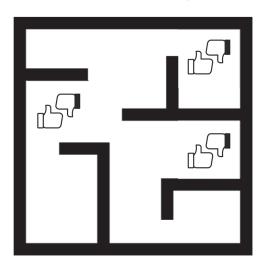
And capture specific preference feedback in that context



How do we make a *like button* for spaces?

How do we get in-context preference data collection that is specific to objectives related to satisfaction with spaces?

The built environment has increased complexity due to the relevance of temporal and spatial dimensions





Post-Occupancy Evaluation Surveys State-of-the-Art



Occupant Indoor Environmental Quality Survey and Building Benchmarking

Occupant surveys are an invaluable source of information regarding occupant satisfaction and workplace effectiveness.

The UC Berkeley CBE Occupant Survey is the gold standard for collecting occupant satisfaction data.

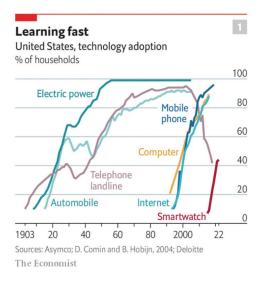
But it's a single-use survey limited use as a tool to 'tune buildings' or build ML models.

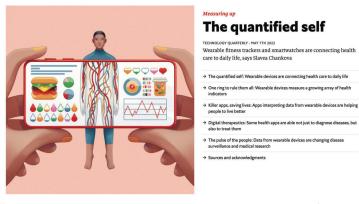
Around 100k survey responses (as of 2017)



https://cbe.berkeley.edu/research/occupant-indoor-survey-and-building-benchmarking/

Growth of Quantified Self and Wearable Devices





"In America smartwatches are catching on as fast as did early mobile phones.

In 2021 about one in four Americans was estimated to own a smartwatch or fitness tracker."



https://www.economist.com/technology-quarterly/2022/05/01/wearable-devices-are-connecting-health-care-to-daily-life

Ecological Momentary Assessment Methodology

Pioneered in medicine, psychology, and marketing, and advertising: Ecological

- Real-world environment and experience
- Ecological validity

Momentary

Real-time assessment and focus

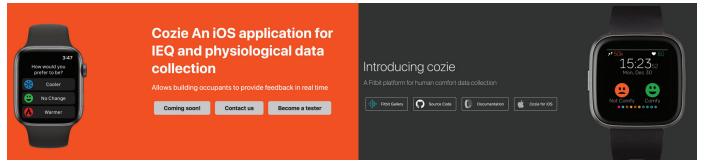
Assessment

- Self-reported
- Repeated, intensive and longitudinal
- Allow analysis of process over time





Cozie Platform: Collecting Occupant Data at Scale in the Built Environment



https://cozie-apple.app/

https://cozie.app/

- Leverage smart watch and phone occupant interaction quickly and easily to characterize built environments
- Open-source, scalable and available for FitBit and Apple Watch
- Collaboration with UC Berkeley CBE



https://github.com/cozie-app

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Micro-survey (EMA) Watch-based Question Flows





Tartarini, F., Miller, C., & Schiavon, S. (2023). Cozie Apple: An iOS mobile and smartwatch application for environmental quality satisfaction and physiological data collection. *Journal of Physics. Conference Series*. https://doi.org/10.1088/1742-6596/2600/14/142003

First Deployment: Intensive Longitudinal Data Collection Across Building/Districts/Cities



Several deployments have created already over 10k occupant feedback responses that are geotagged to indoor and outdoor locations



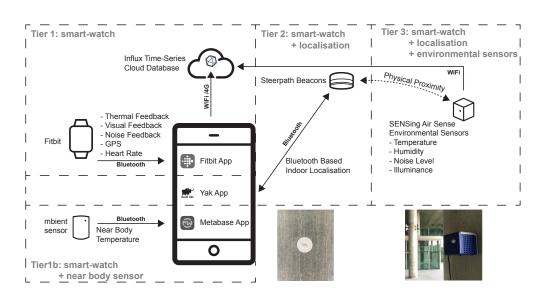
Jayathissa P, Quintana M, Abdelrahman M, Miller C. Humans-as-a-Sensor for Buildings—Intensive Longitudinal Indoor Comfort Models. Buildings. 2020;10: 174. https://doi.org/10.3390/buildings10100174
Jayathissa, P., Quintana, M., Sood, T., Nazarian, N., & Miller, C. (2019). Is your clock-face cozie? A smartwatch methodology for the in-situ collection of occupant comfort data. *Journal of Physics. Conference Series*, 1343(1), 012145.

https://doi.org/10.1088/1742-6596/1343/1/012145

Cozie Data Collection Infrastructure



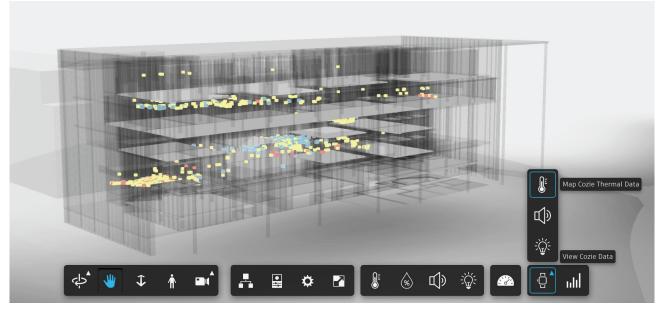






Jayathissa P, Quintana M, Abdelrahman M, Miller C. Humans-as-a-Sensor for Buildings—Intensive Longitudinal Indoor Comfort Models. Buildings. 2020;10: 174. https://doi.org/10.3390/buildings10100174

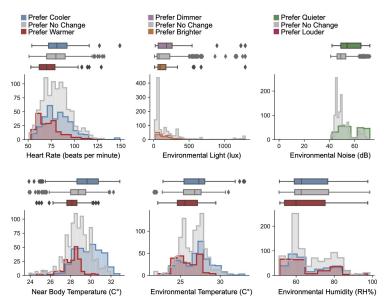
Scalable Field-based Data Collection





Jayathissa P, Quintana M, Abdelrahman M, Miller C. Humans-as-a-Sensor for Buildings—Intensive Longitudinal Indoor Comfort Models. Buildings. 2020;10: 174. https://doi.org/10.3390/buildings10100174

Environmental, Heart Rate, and Near-body Temperature IoT

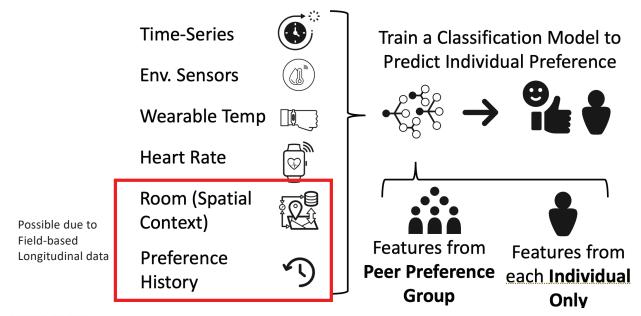


- Environmental, physiological and near-body variables
- There are indications of sensors can be meaningful, but are not capturing everything



Jayathissa P, Quintana M, Abdelrahman M, Miller C. Humans-as-a-Sensor for Buildings—Intensive Longitudinal Indoor Comfort Models. Buildings. 2020;10: 174. https://doi.org/10.3390/buildings10100174

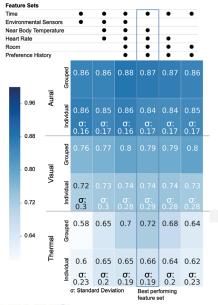
Building New Types of ML-driven Comfort Preference Prediction Models





Jayathissa P, Quintana M, Abdelrahman M, Miller C. Humans-as-a-Sensor for Buildings—Intensive Longitudinal Indoor Comfort Models. Buildings. 2020;10: 174. https://doi.org/10.3390/buildings10100174

Thermal Comfort Prediction Results using Intensive Longitudinal Data

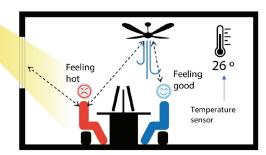


- The model accuracy was highest with Time, Near-body, HR, Room, and Preference History
- Most accurate models didn't include environmental sensors
- Grouped models consistently outperform individual models

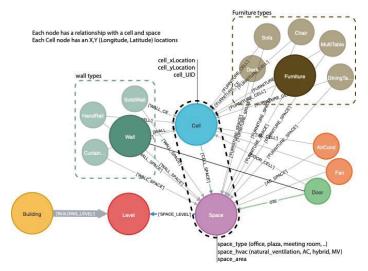


Jayathissa P, Quintana M, Abdelrahman M, Miller C. Humans-as-a-Sensor for Buildings—Intensive Longitudinal Indoor Comfort Models. Buildings. 2020;10: 174. https://doi.org/10.3390/buildings10100174

Next-Generation Personal Comfort Models using BIM and Spatial Proximity



Can the proximity of occupants different parts of the building context be good predictors of comfort?

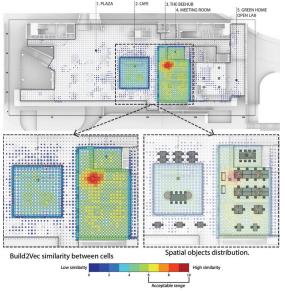


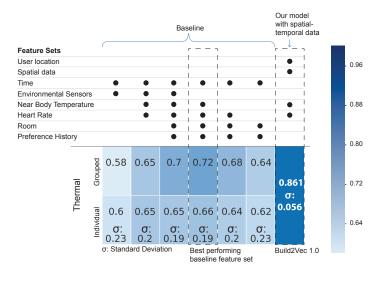


Abdelrahman, M. M., Chong, A., & Miller, C. (2022). Personal thermal comfort models using digital twins: Preference prediction with BIM-extracted spatial–temporal proximity data from Build2Vec. *Building and Environment, 207*(108532), 108532. https://doi.org/10.1016/j.buildenv.2021.108532

SOE4 - Level 3

Next-Generation Personal Comfort Models using BIM and Spatial Proximity

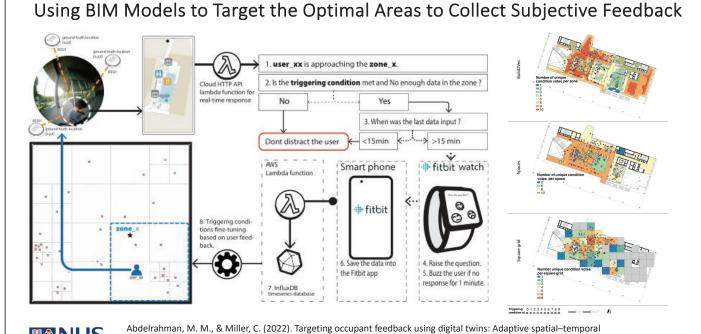






Abdelrahman, M. M., Chong, A., & Miller, C. (2022). Personal thermal comfort models using digital twins: Preference prediction with BIM-extracted spatial-temporal proximity data from Build2Vec. *Building and Environment*, 207(108532), 108532. https://doi.org/10.1016/j.buildenv.2021.108532

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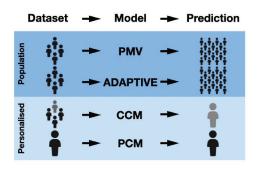


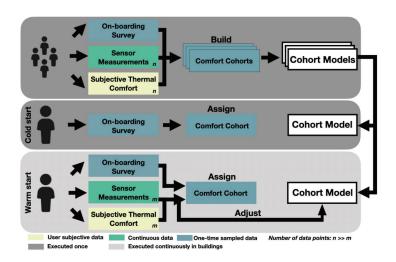
thermal preference sampling to optimize personal comfort models. Building and Environment, 218, 109090.

https://doi.org/10.1016/j.buildenv.2022.109090

Finding Cohort-based Comfort Models for different 'Personality Types'

Creating 'phenotypes' of comfort in buildings to generalize across those that don't wear smart-watches







Quintana, M., Schiavon, S., Tartarini, F., Kim, J., & Miller, C. (2023). Cohort comfort models — Using occupant's similarity to predict personal thermal preference with less data. *Building and Environment*, *227*, 109685. https://doi.org/10.1016/j.buildenv.2022.109685

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Thinking Beyond Thermal Comfort



Building's Impact on Movement



Noise, Distraction and Privacy



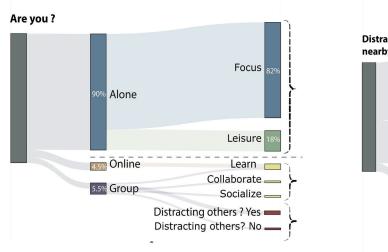
Infection Risk Perception

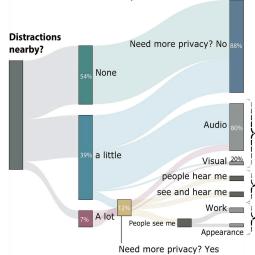
We are working on question flows that enhance the ability to learn about buildings from many dimensions!



Miller C, Christensen R, Leong JK, Abdelrahman M, Tartarini F, Quintana M, et al. Smartwatch-based ecological momentary assessments for occupant wellness and privacy in buildings. arXiv [cs.HC]. 2022. Available: http://arxiv.org/abs/2208.06080 - Presented at Indoor Air 2022

Results from Privacy and Distraction Survey

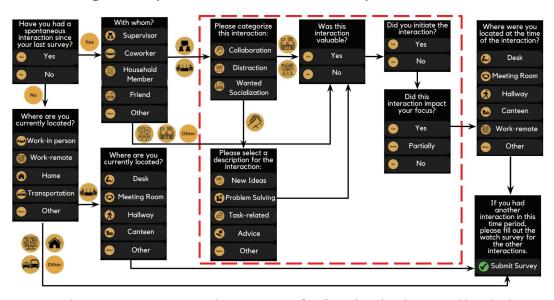






Miller C, Christensen R, Leong JK, Abdelrahman M, Tartarini F, Quintana M, et al. Smartwatch-based ecological momentary assessments for occupant wellness and privacy in buildings. arXiv [cs.HC]. 2022. Available: http://arxiv.org/abs/2208.06080 - Presented at Indoor Air 2022

Characterizing Occupant Interaction for Hybrid Work

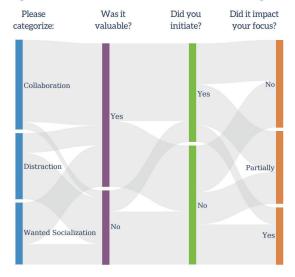




Maisha, K., Frei, M., Quintana, M., Chua, Y. X., Jain, R., & Miller, C. (2023). Utilizing wearable technology to characterize and facilitate occupant collaborations in flexible workspaces. *Journal of Physics. Conference Series*, 2600(14), 142009. https://doi.org/10.1088/1742-6596/2600/14/142009

Characterizing Occupant Interaction for Hybrid Work

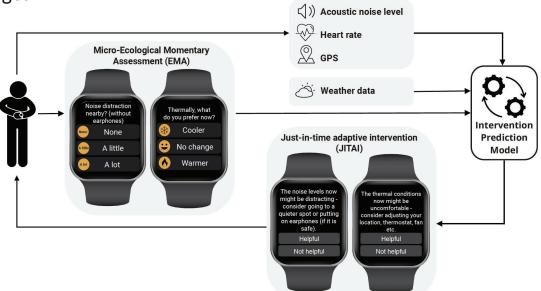
For spontaneous interactions with either a coworker or supervisor:





Maisha, K., Frei, M., Quintana, M., Chua, Y. X., Jain, R., & Miller, C. (2023). Utilizing wearable technology to characterize and facilitate occupant collaborations in flexible workspaces. *Journal of Physics. Conference Series*, 2600(14), 142009. https://doi.org/10.1088/1742-6596/2600/14/142009

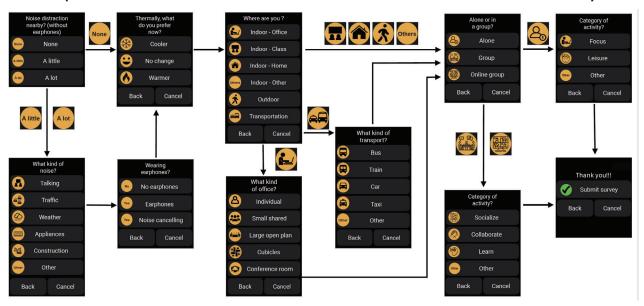
Our current experiment: Just-in-time Adaptive Intervention (JITAI) Messages





Miller, C., Chua, Y. X., Frei, M., & Quinana, M. (November 9-10 2022). Towards smartwatch-driven just-in-time adaptive interventions (JITAI) for building occupants. The 9th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation. https://doi.org/10.1145/3563357.3566135

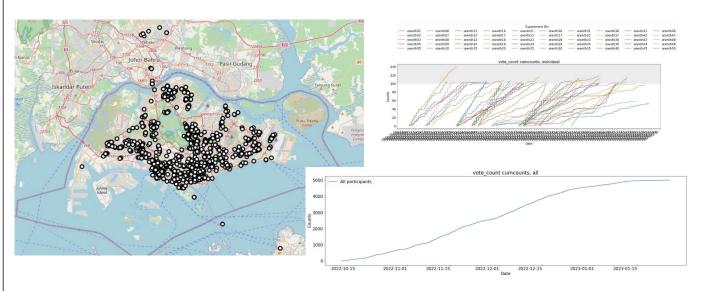
Development of Conditional Question Flows and 'Chat-bot' Style





Miller, C., Chua, Y. X., Frei, M., & Quinana, M. (November 9-10 2022). Towards smartwatch-driven just-in-time adaptive interventions (JITAI) for building occupants. *The 9th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*. https://doi.org/10.1145/3563357.3566135

Scalability of Data Collection across Singapore

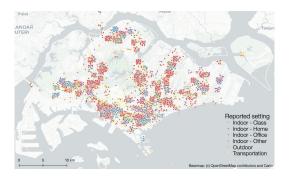




Miller, C., Chua, Y. X., Frei, M., & Quinana, M. (November 9-10 2022). Towards smartwatch-driven just-in-time adaptive interventions (JITAI) for building occupants. *The 9th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation*. https://doi.org/10.1145/3563357.3566135

Cool, Quiet City Competition – Creating Models for Recommendations





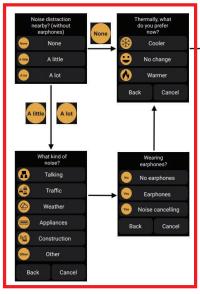
This competition includes the city-scale collection of 9,808 smartwatch-driven micro-survey responses that were collected alongside 2,659,764 physiological and environmental measurements from 98 people using the open-source Cozie-Apple platform

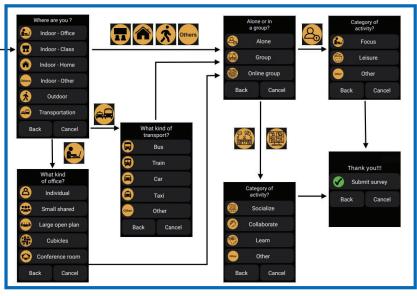


https://www.kaggle.com/competitions/cool-quiet-city-competition/

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The New Idea of using an ML Competition using Wearable Data





National University of Singapore

Prediction Objectives

Context Information - Part of the Training Data

Building New Types of ML-driven Comfort Preference Prediction Models

Time Stamp

Outdoor Conditions



Noise, Heartrate, and other Physiological data from the watch





Spatial Context Features



Historical training data from **Context Questions** On-Boarding Survey Information



Train a Classification Model to **Predict Individual Preference**











Miller, C., Quintana, M., Frei, M., Chua, Y. X., Fu, C., Picchetti, B., Yap, W., Chong, A., & Biljecki, F. (2023). Introducing the Cool, Quiet City Competition: Predicting Smartwatch-Reported Heat and Noise with Digital Twin Metrics. Proceedings of the 10th ACM International Conference on Systems for Energy-Efficient Buildings, Cities, and Transportation, 298–299. https://doi.org/10.1145/3600100.3626269

Coming soon: HEATS — Heat Exposure, AcTivity and Sleep Study











Jason Lee and June Lo **NUS Medicine and** Psychology

Univ. of Sydney

Thomas Parkinson Stefano Schiavon and Hui Zhang UC Berkeley Center for the Built **Environment**



Coming soon: HEATS – Heat Exposure, AcTivity and Sleep Study





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The Vision: Community-driven Scaled-up Data Collection and Sharing!



The dream is to collect **millions of data points** from *hundreds of thousands of people* worldwide to determine what makes people tick when it comes to satisfaction in buildings



Quintana, M., Abdelrahman, M., Frei, M., Tartarini, F., & Miller, C. (2021). Longitudinal personal thermal comfort preference data in the wild. *Proceedings of the 19th ACM Conference on Embedded Networked Sensor Systems*, 556–559. https://doi.org/10.1145/3485730.3493693

Acknowledgements

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Questions/Comments? clayton@nus.edu.sg



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