

Real-time Analytics for Internet of Sports

| *Marie Curie European Training Network*

ESR13

USING WEARABLE TECHNOLOGIES TO UNDERSTAND SOCIAL CONTEXT

Christina Karagianni, Aristotle University of Thessaloniki (AUTH)

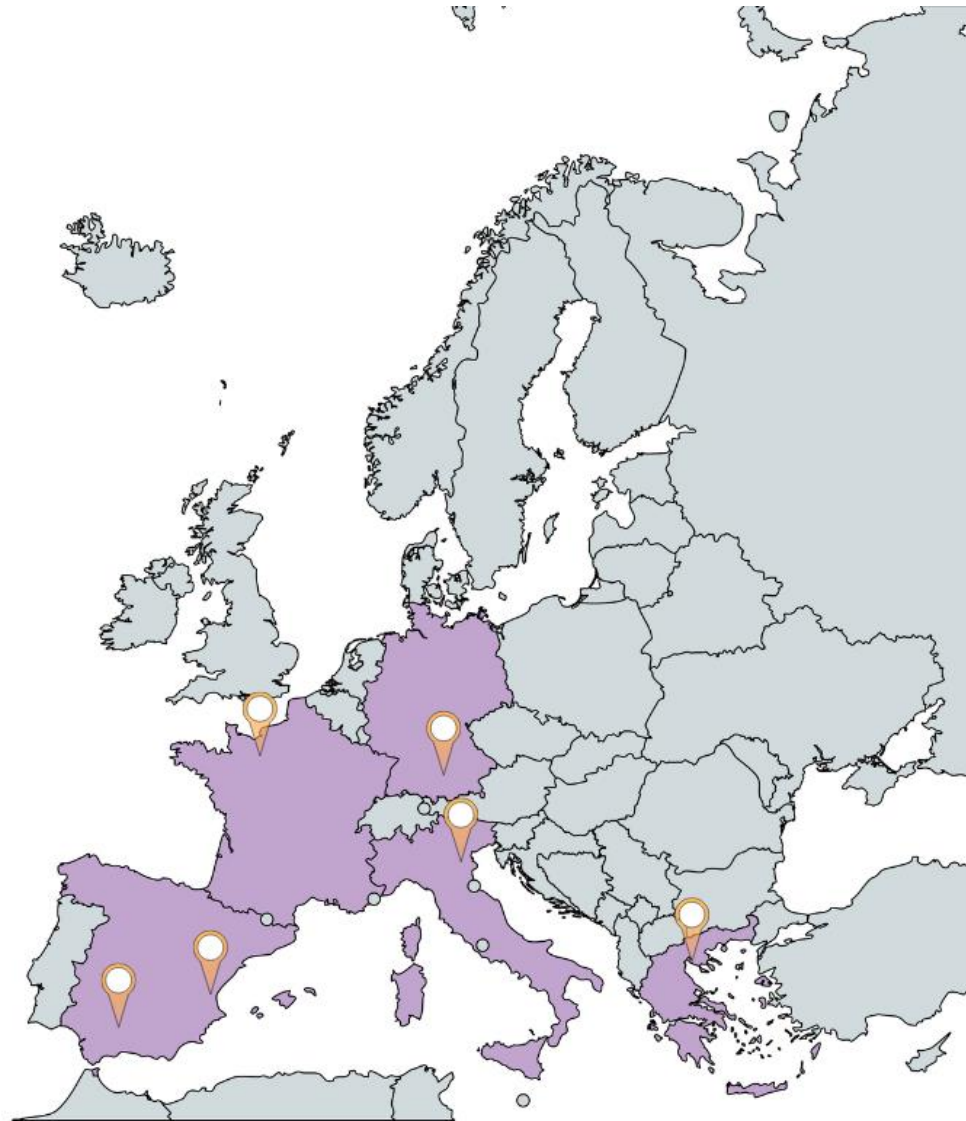
Outline

- Few words about me
- First steps
- Research interests



Few words about me

- BSc in **Physics** (AUTH)
- Erasmus Mundus Joint MSc in **Nuclear physics** (US, UNICAEN, UNIPD)
- Internships
 - Max-Planck-Institute for Plasma Physics, Munich
 - Instituto de Física Corpuscular, Valencia
 - Grand Accélérateur National d'Ions Lourds, Caen



Few words about me

- RAIS ESR – Using wearable technologies to understand social context (AUTH)
- MSc Student in Advanced Computer and Communication Systems (AUTH)



LifeSnaps Dataset – The Study Design



Participants



SEMA3 Data

Ecological Momentary Assessments

- Context and Mood Survey
- Step Goal Survey

Fitbit Sense

Automatically Synced Data

- Sleep
- Temperature
- Distance
- Exercise
- Heart Rate
- Stress
- Mindfulness session

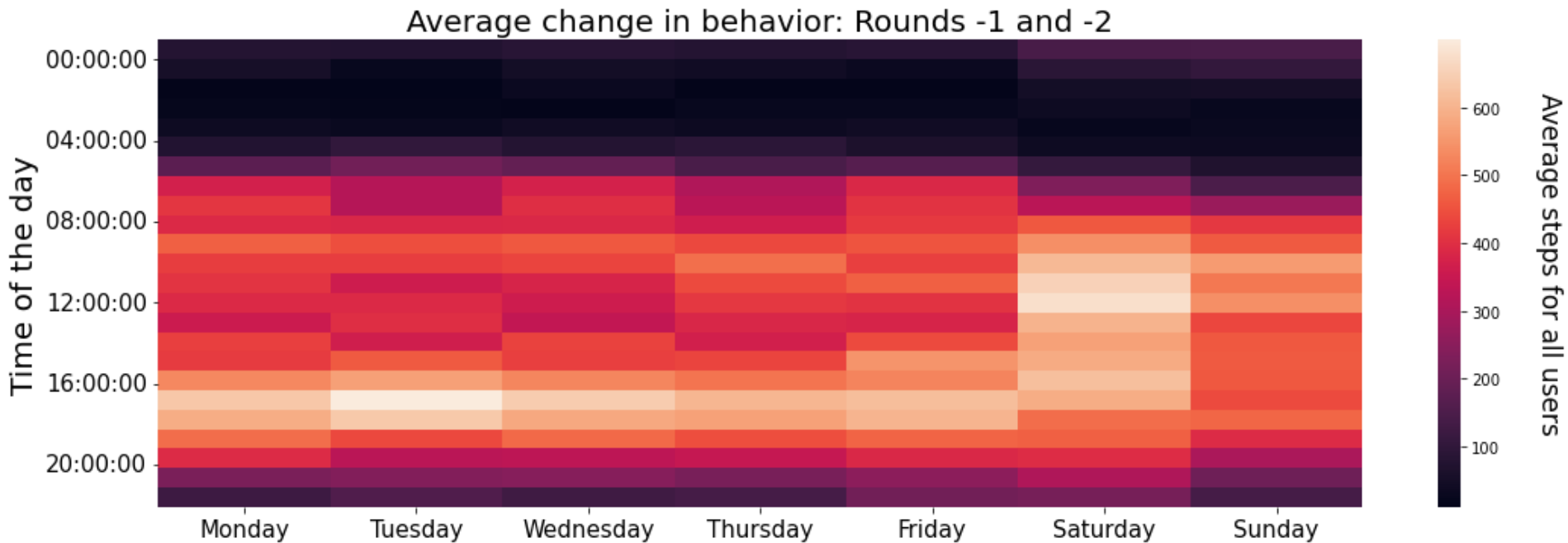
Surveys Data

Self Reported Data

- Health
- Behavioral and Psychological Traits
- Demographics

LifeSnaps Dataset

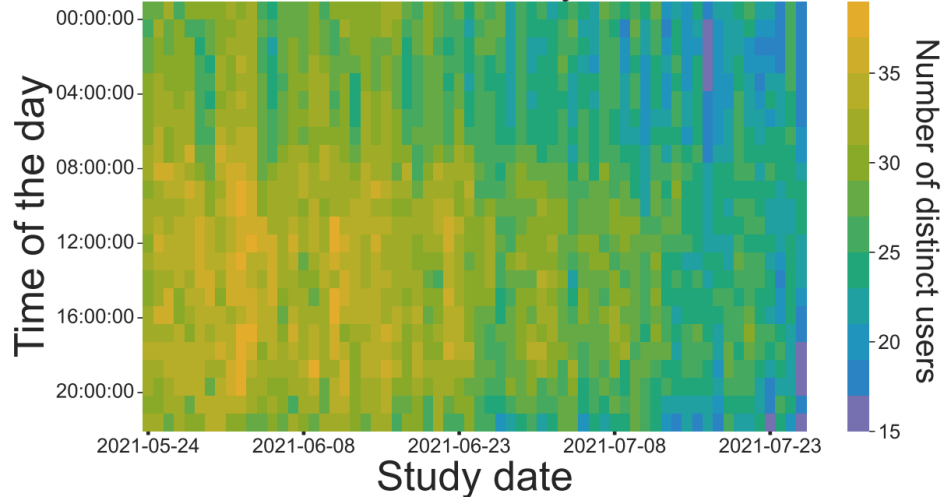
When and how much have our participants walked?



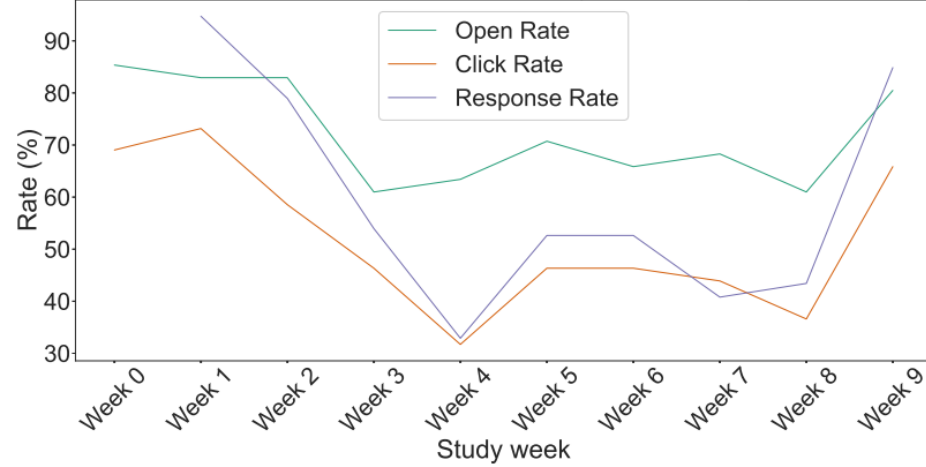
Physical inactivity has been identified as the fourth leading risk factor for global mortality^[1].

LifeSnaps Dataset – Data Availability and User Engagement

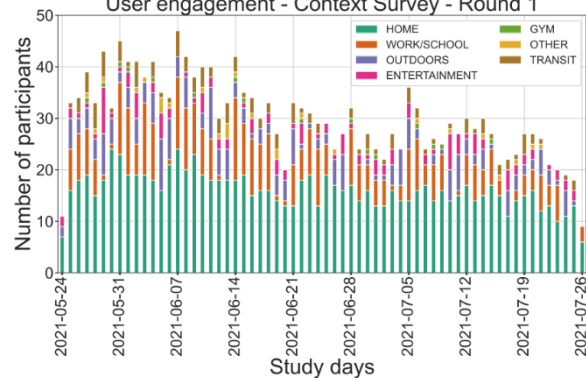
Fitbit Data Availability: Round 1



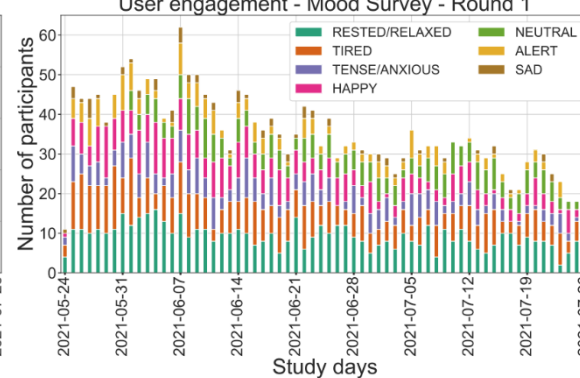
Mail Communication Rates Over Time (excl. Resends) - Round 1



User engagement - Context Survey - Round 1



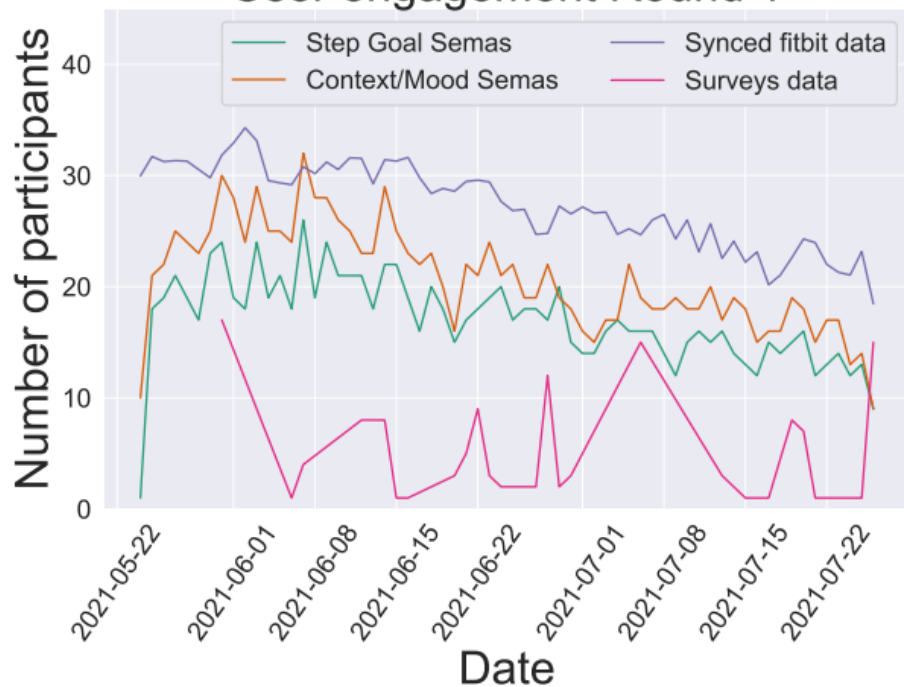
User engagement - Mood Survey - Round 1



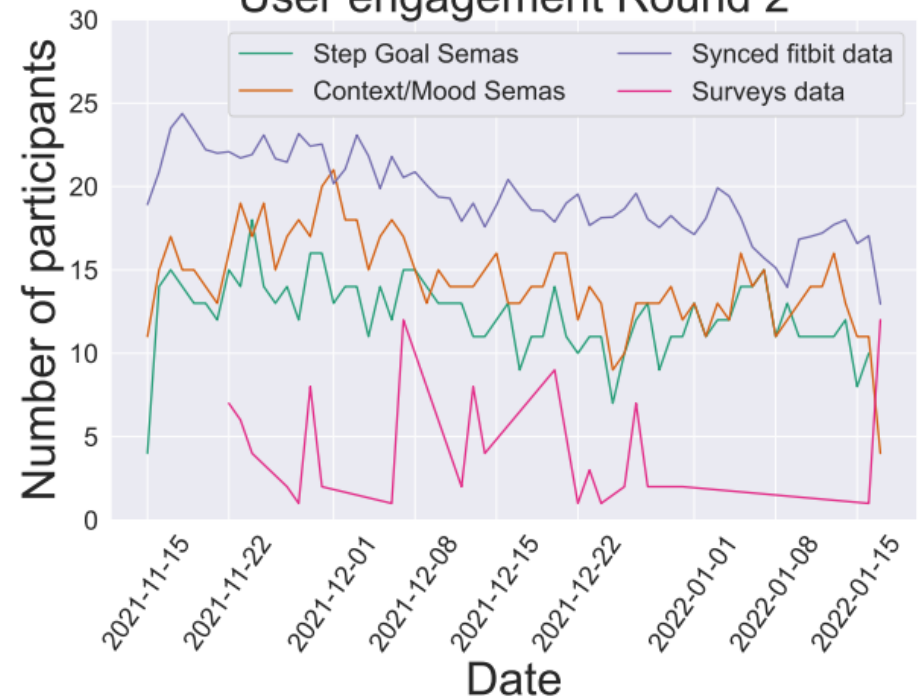
- Outstanding **user engagement** and **study's duration** compared to other studies [2], [3].
- The mean user engagement rises to 41.37 days, corresponding to 73% of the total experimental days.

LifeSnaps Dataset – User Engagement

User engagement Round 1



User engagement Round 2



Research Interests

- **Detecting behavior changes**

Different User → Different Behavior (between-person variability)^[4]
Individuals show changes in their own patterns over time (within-person variability)^[4].

- **Mental health area**

Wearable devices and mobile phone sensors can be used complementarily to self-reports, collecting data unobtrusively in-the-wild^{[5], [6], [7]}.

- Identifying patterns^[8], developing prediction models^[9].

Bibliography

- [1] <https://www.who.int/data/gho/indicator-metadata-registry/imr-details/3416>
- [2] Hershman, S. G ., et. al. (2019). Physical activity, sleep and cardiovascular health data for 50,000 individuals from the MyHeart Counts Study. *Scientific Data*, 6(1). <https://doi.org/10.1038/s41597-019-0016-7>
- [3] Chan, Y. F. Y., et. al. (2018). Data Descriptor: The asthma mobile health study, smartphone data collected using ResearchKit. *Scientific Data*, 5. <https://doi.org/10.1038/sdata.2018.96>
- [4] Wang, W., et. al. (2018). Sensing Behavioral Change over Time. *Proceedings of the ACM on Interactive, Mobile, Wearable and Ubiquitous Technologies*, 2(3), 1–21. <https://doi.org/10.1145/3264951>
- [5] Kang, M., & Chai, K. (2022). Wearable Sensing Systems for Monitoring Mental Health. In *Sensors* (Vol. 22, Issue 3). MDPI. <https://doi.org/10.3390/s22030994>
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- [7] Wang, R., et. Al. (2016). CrossCheck: Toward passive sensing and detection of mental health changes in people with schizophrenia. *UbiComp 2016 - Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing*, 886–897. <https://doi.org/10.1145/2971648.2971740>
- [8] Sano, A., et. al. (2015). Recognizing academic performance, sleep quality, stress level, and mental health using personality traits, wearable sensors and mobile phones. *2015 IEEE 12th International Conference on Wearable and Implantable Body Sensor Networks, BSN 2015*. <https://doi.org/10.1109/BSN.2015.7299420>
- [9] Jaques, N., et. al. (2016). Multi-task Learning for Predicting Health , Stress , and Happiness.

Beneficiaries / Partners

BENEFICIARIES



PARTNERS



Acknowledgement

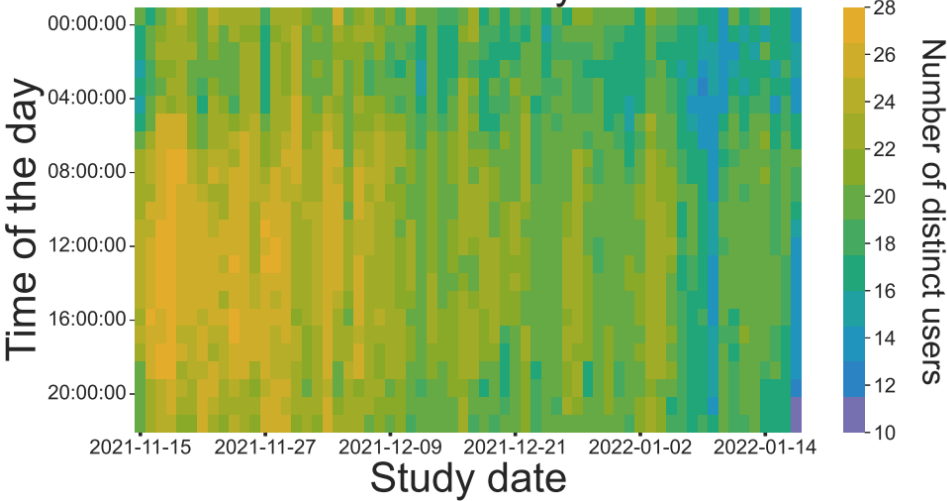


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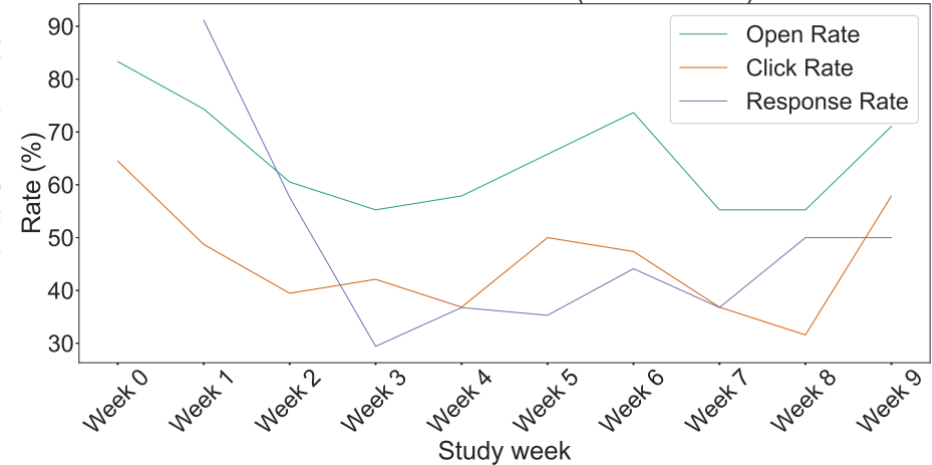
Back-up slides

LifeSnaps Dataset – Data Availability and User Engagement

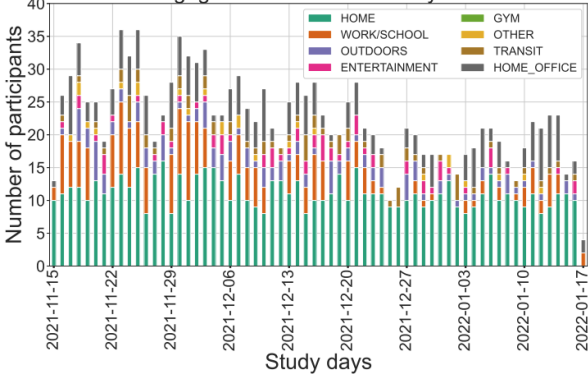
Fitbit Data Availability: Round 2



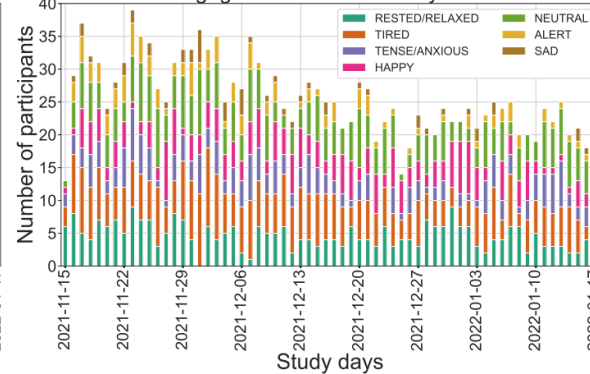
Mail Communication Rates Over Time (excl. Resends) - Round 2



User engagement - Context Survey - Round 2



User engagement - Mood Survey - Round 2



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