Cardiovascular interactions during head-up tilt test by transfer entropy between ordinal patterns of heart rate and blood pressure

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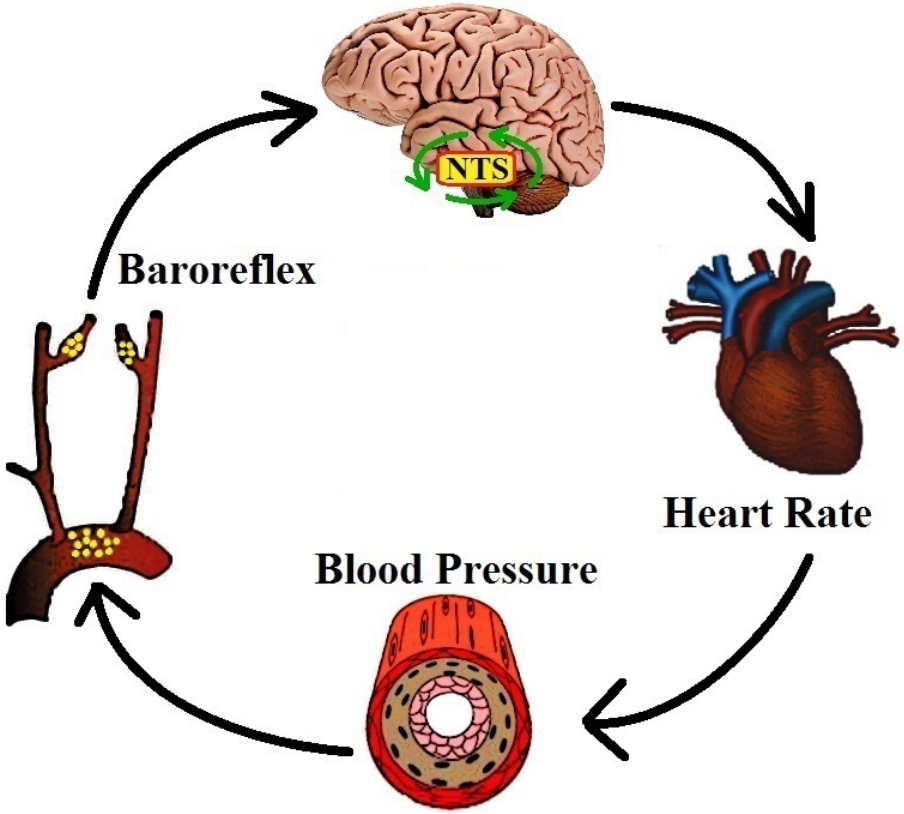
[6] *RIKEN Brain Science Institute, Wako-shi, Japan*
University of Tokyo, Graduate School of Education, Tokyo, Japan

Physiological background



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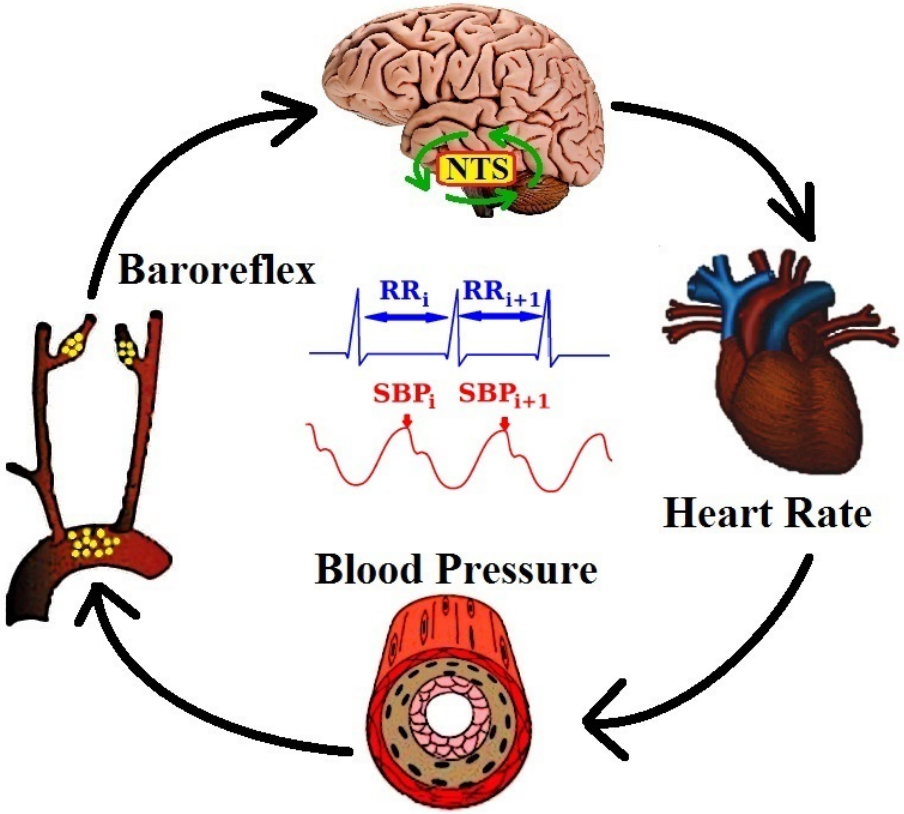

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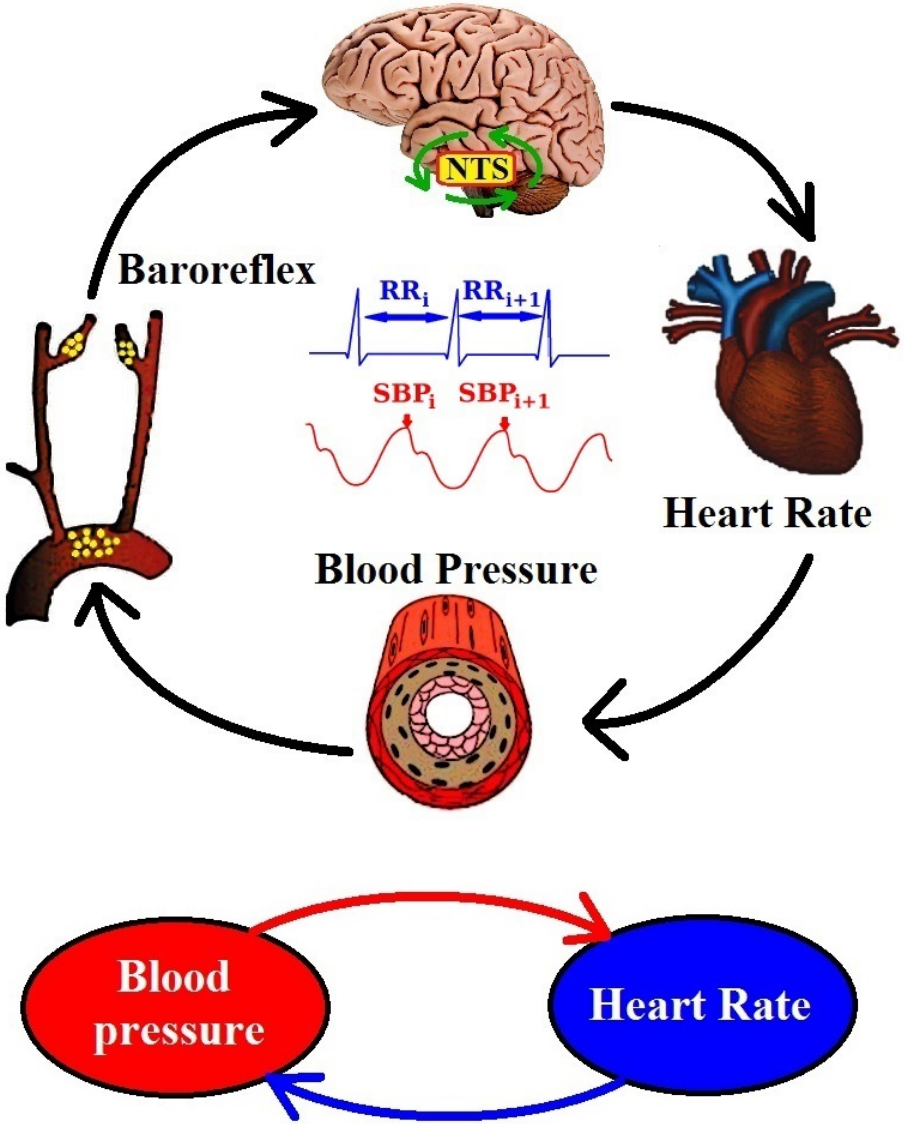

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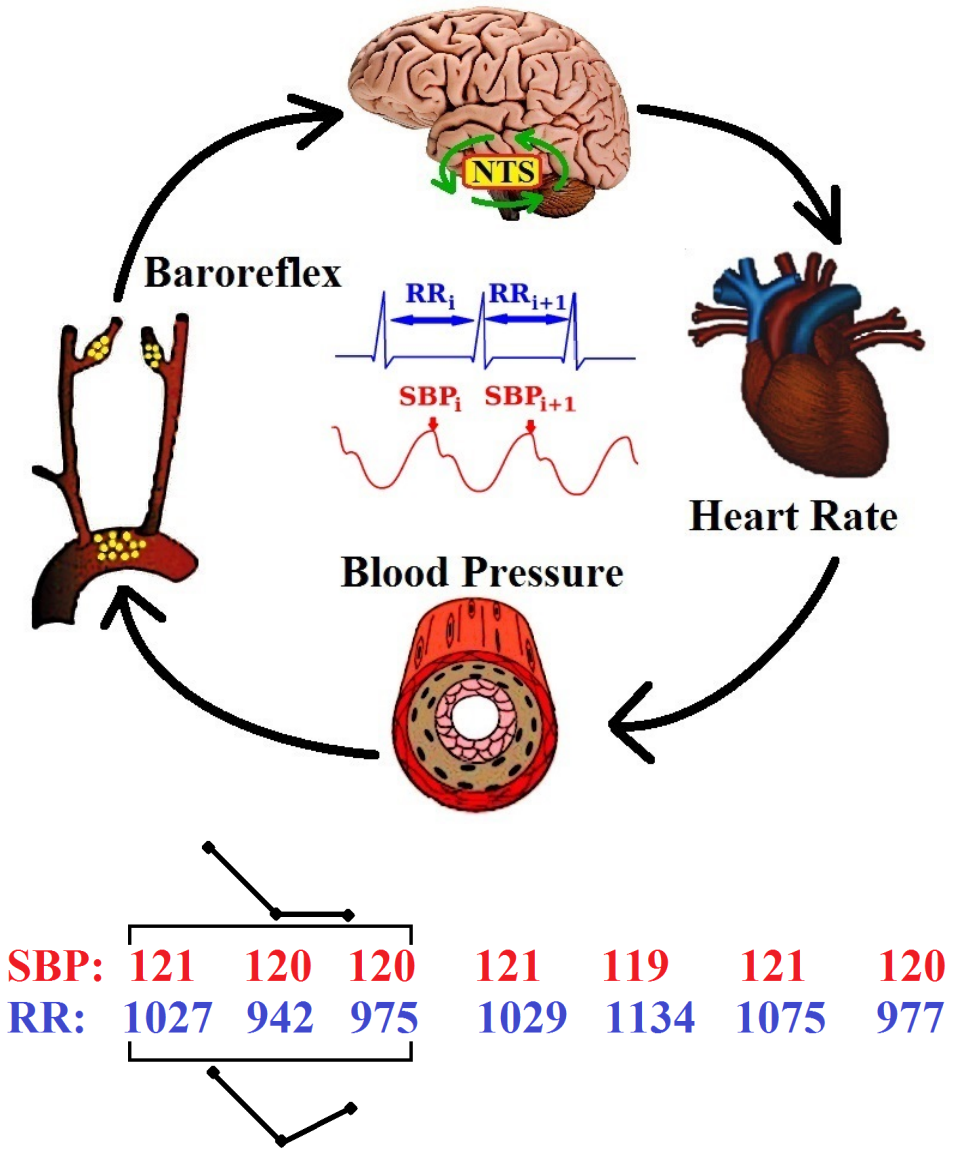

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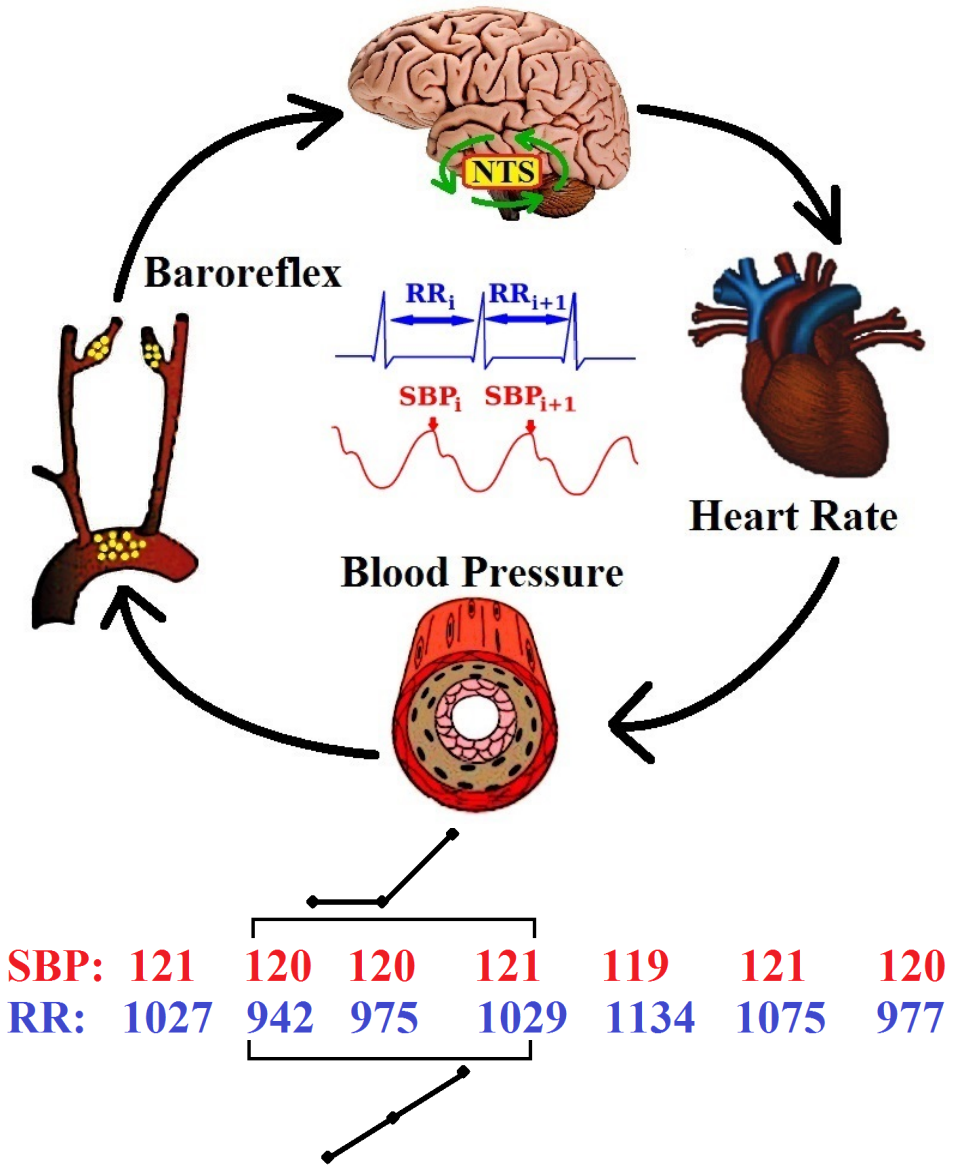

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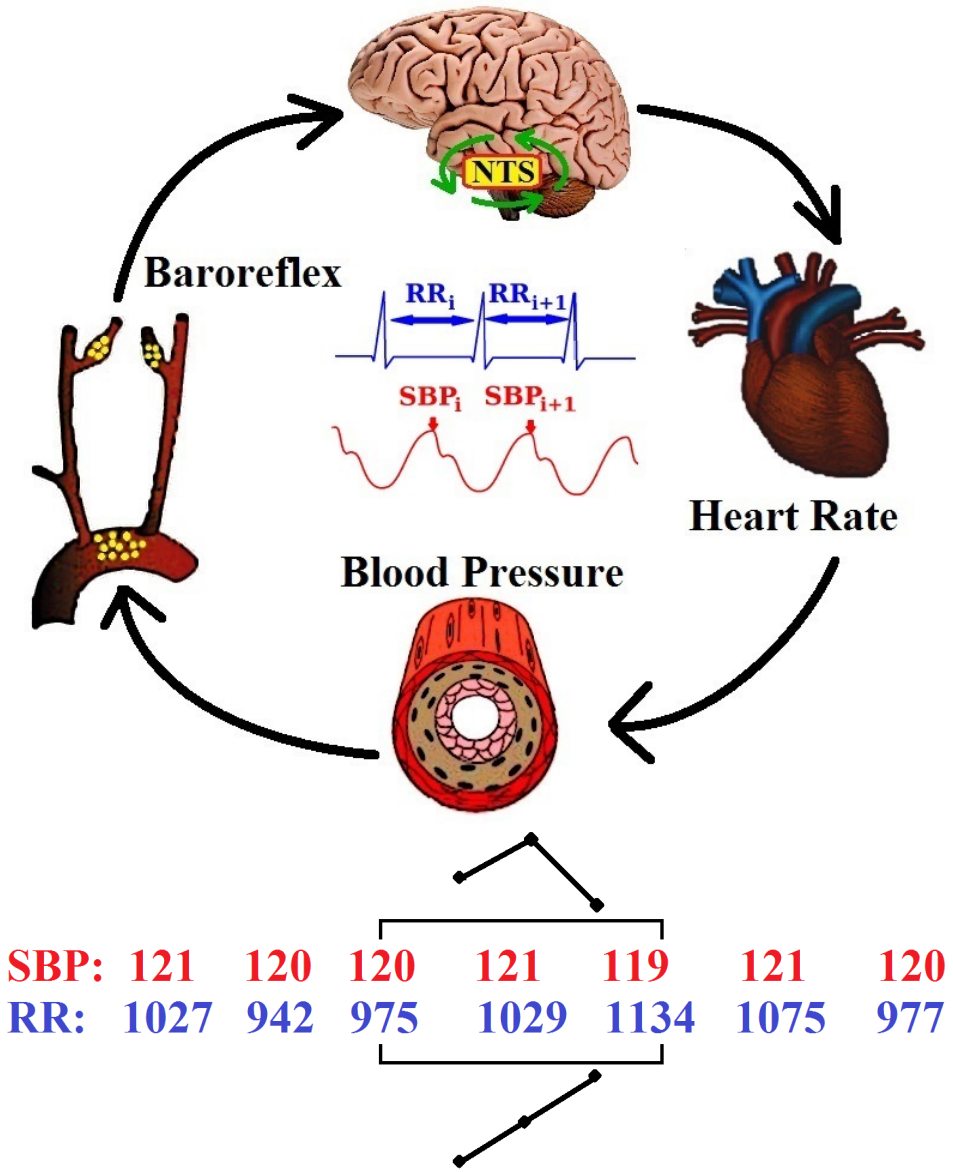

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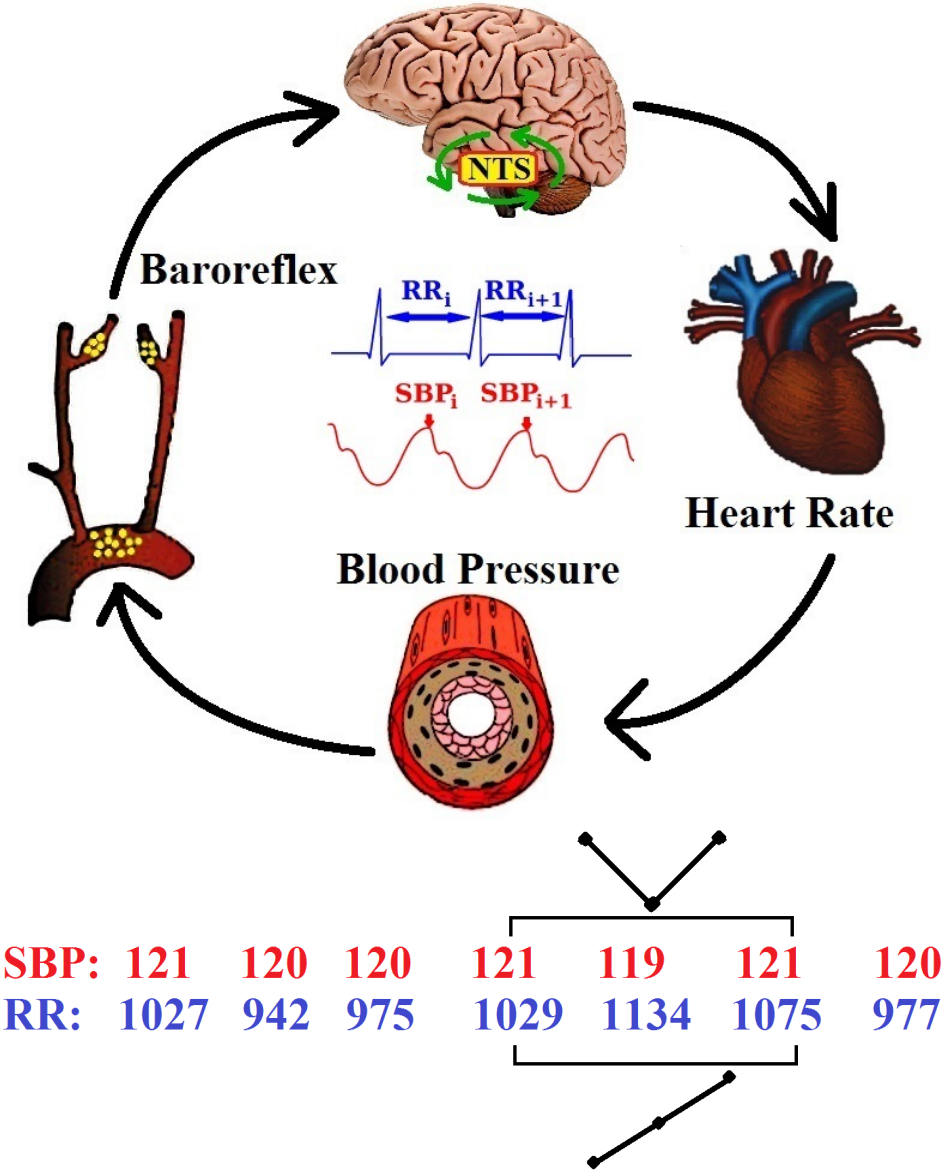

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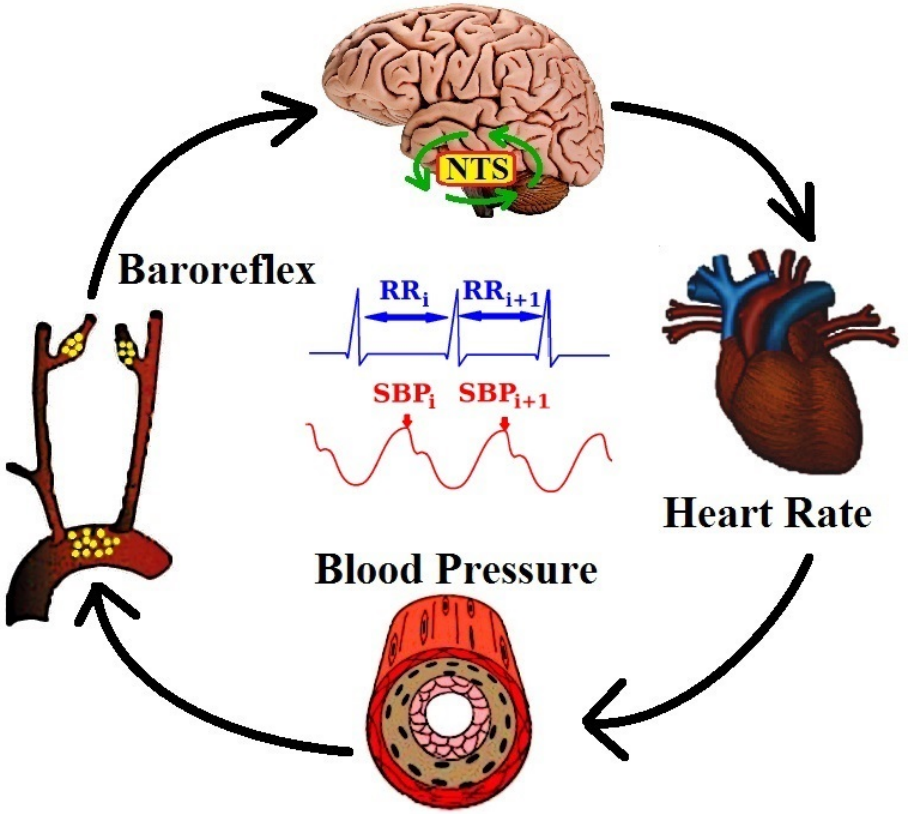
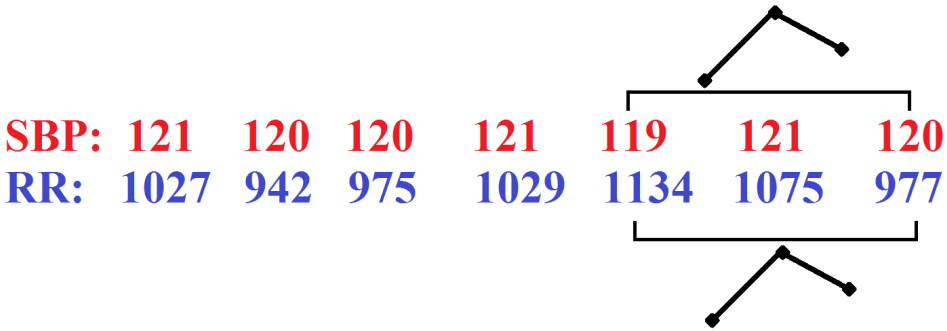
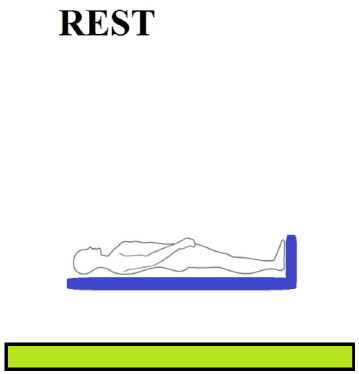




The head-up tilt test



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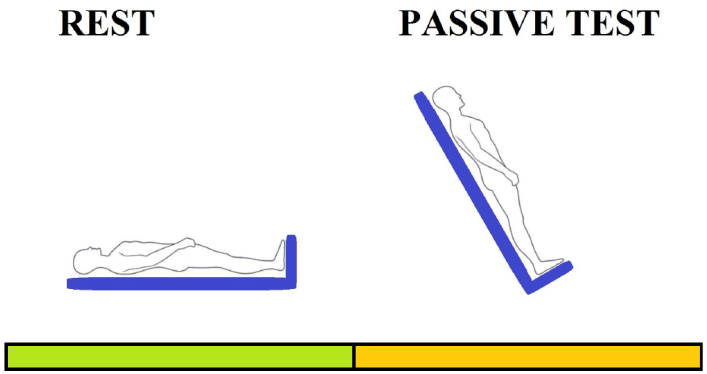

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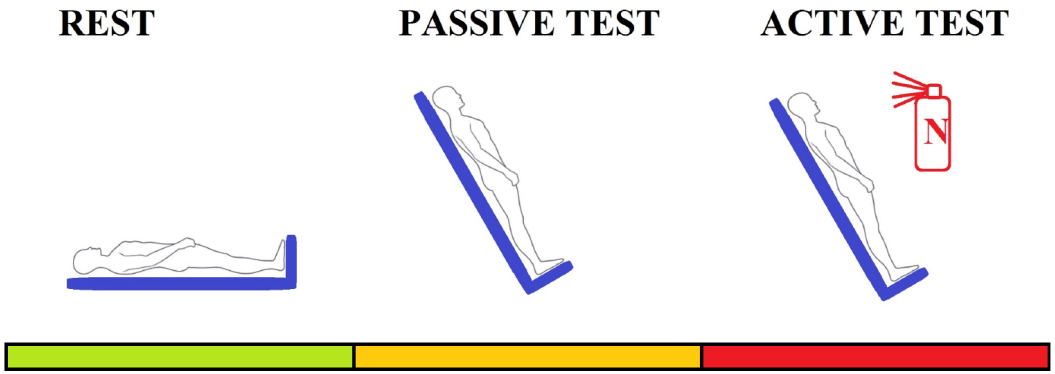

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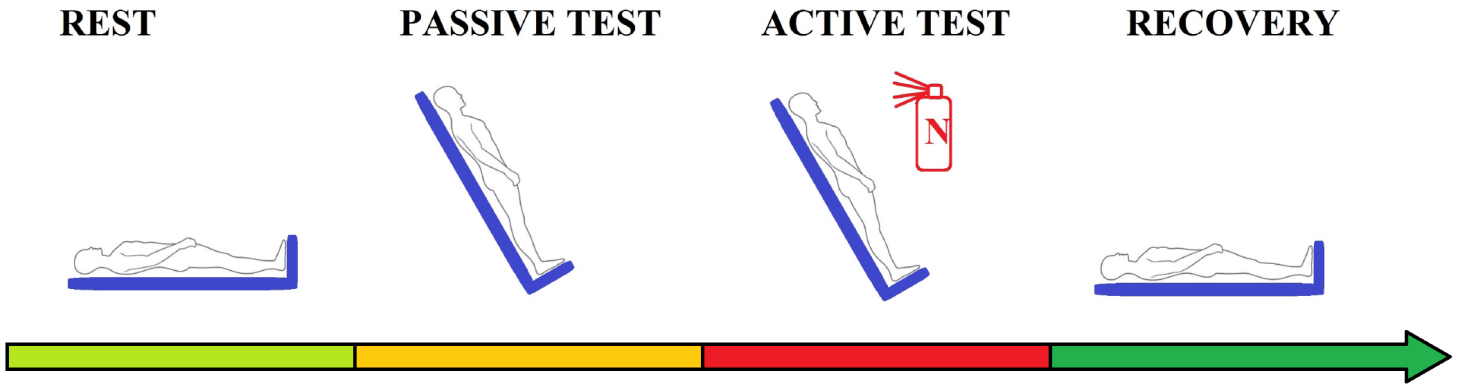

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4. Recovery – rest in supine position

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- 28 healthy volunteers (14 females);
- age: 20-39 yr, median age: 23 yr;
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VVS - patients group

- 54 people with syncope in daily life (37 females);
- age: 18-44 yr, median age: 23 yr;
- history of fainting;
- positive result of the HUT test.

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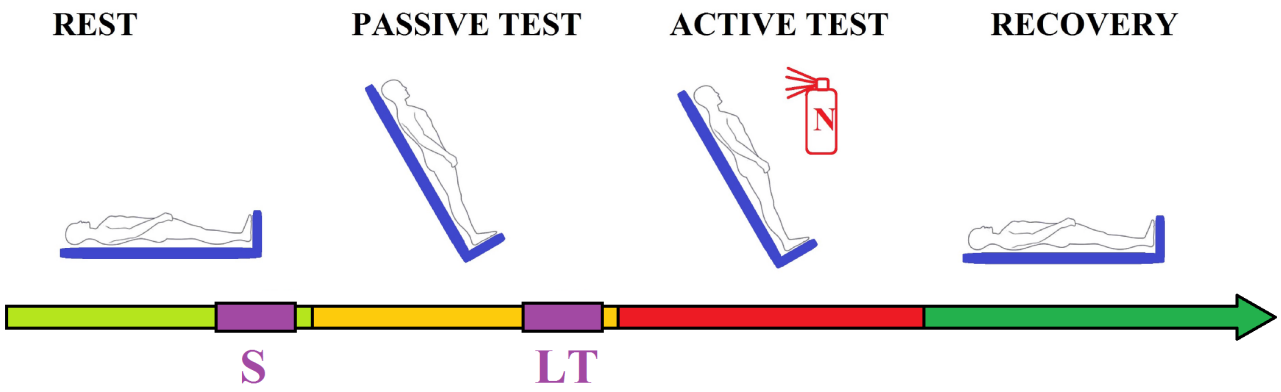

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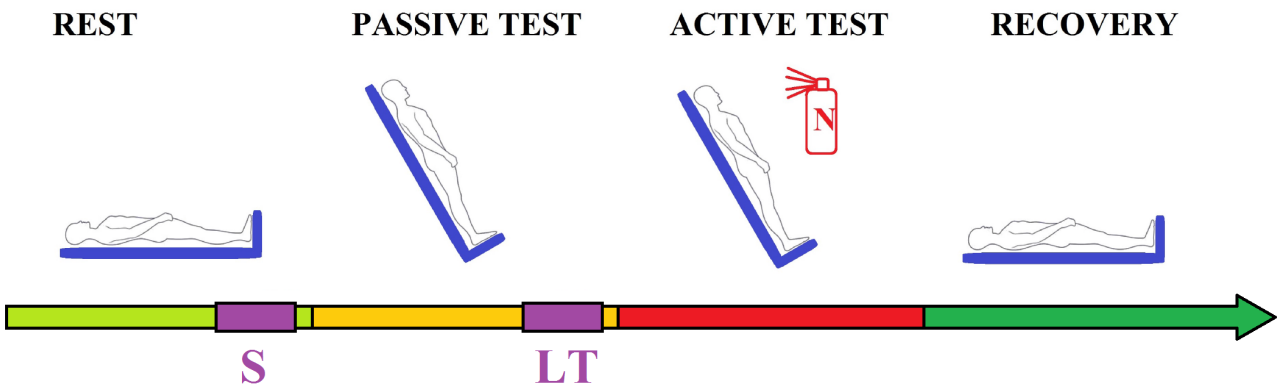

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- Each time window contained 300 pairs of (RR, SBP) values.

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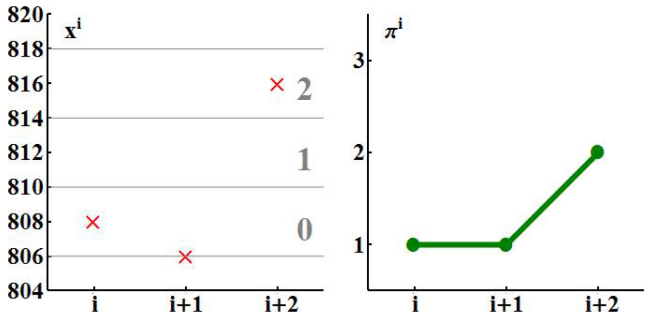

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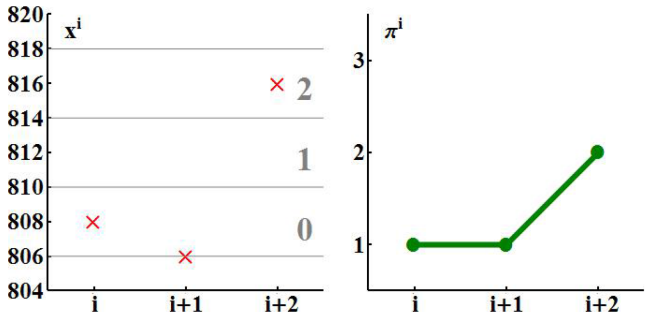
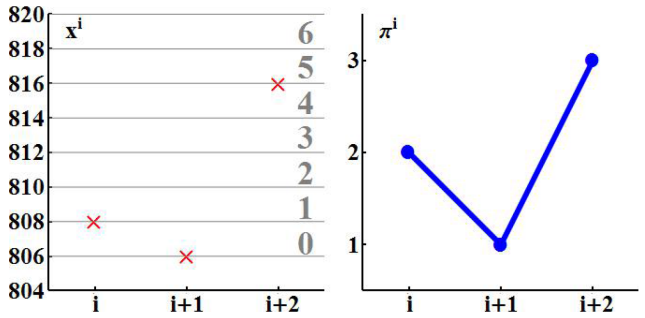
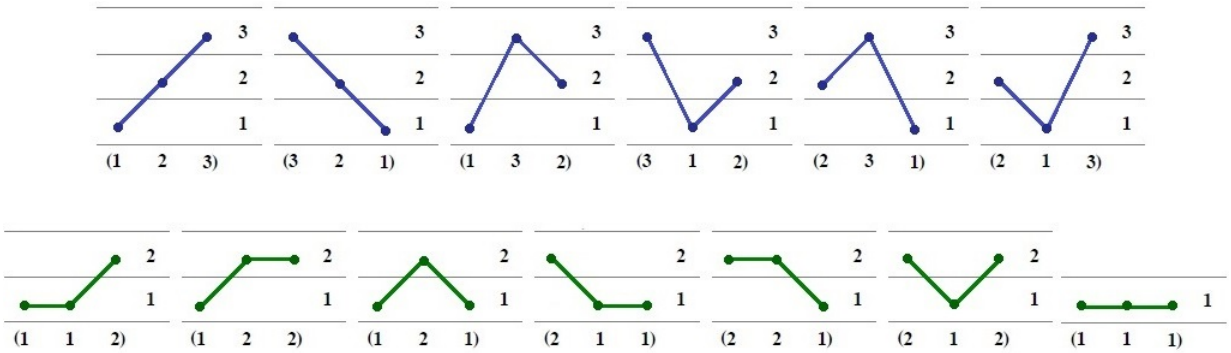
$\phi^i = (1, 0, 5)$
$\pi^i = (2, 1, 3)$





Ordinal pattern distribution



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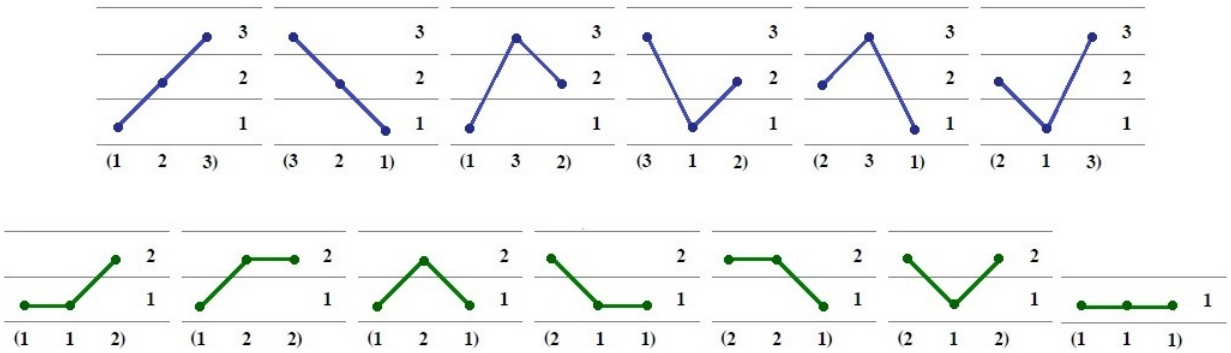

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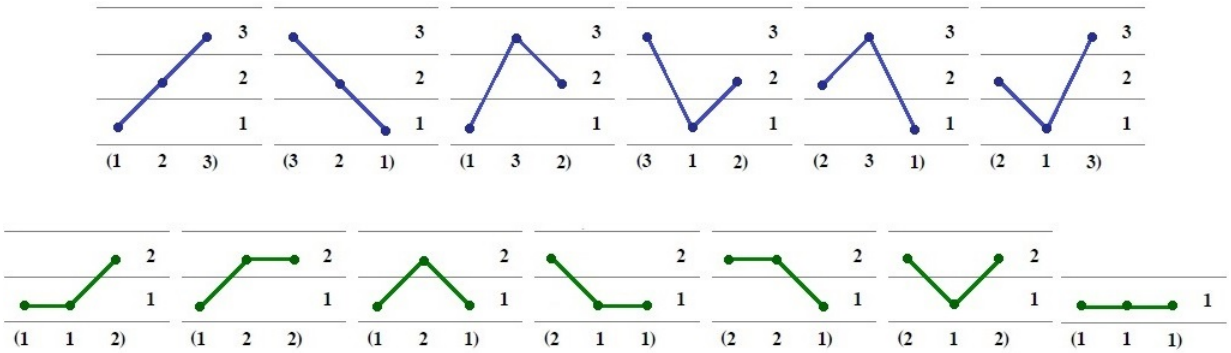

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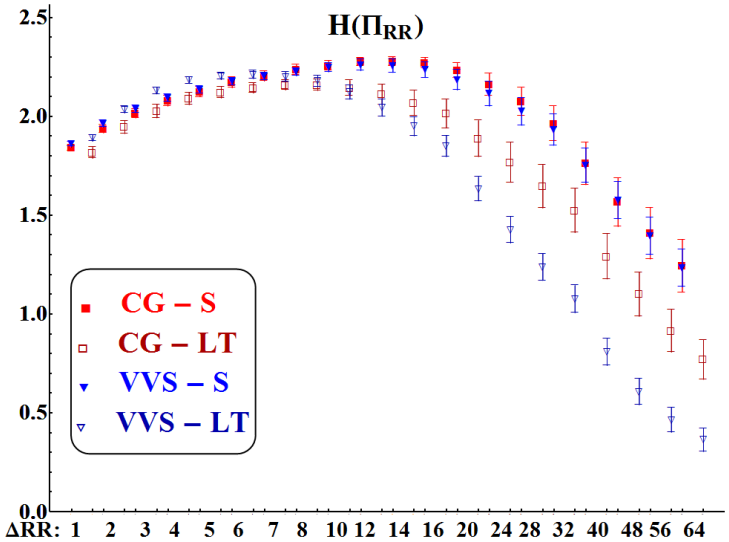

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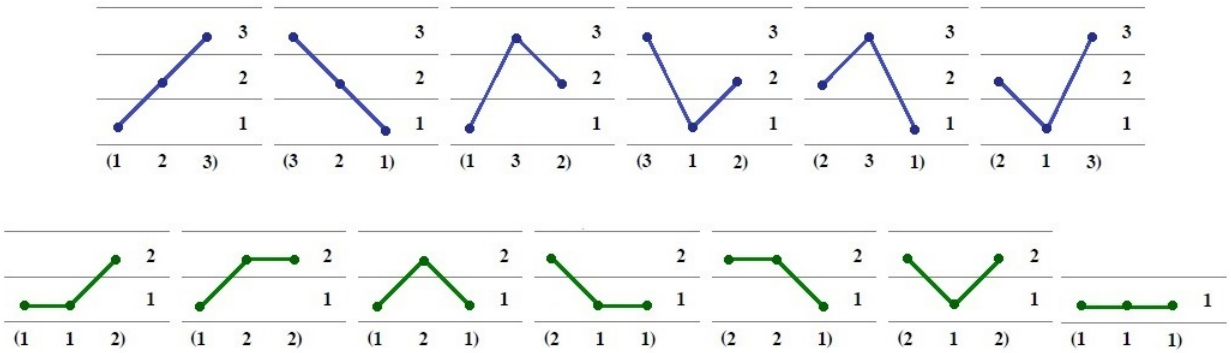

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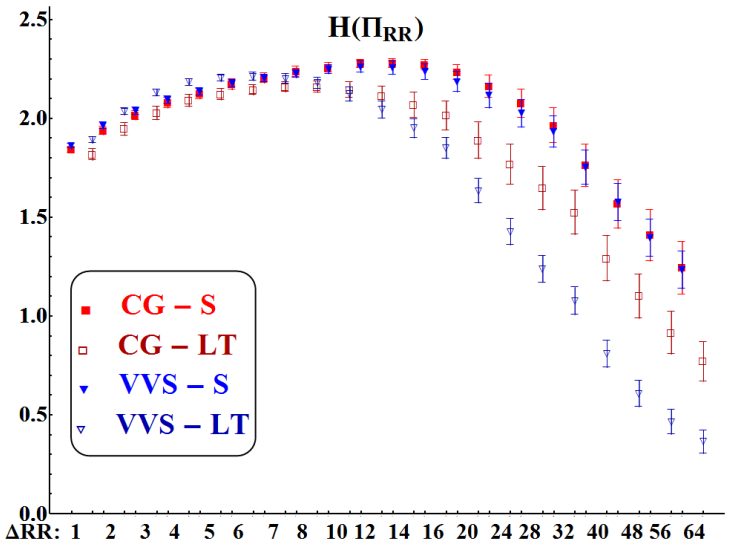

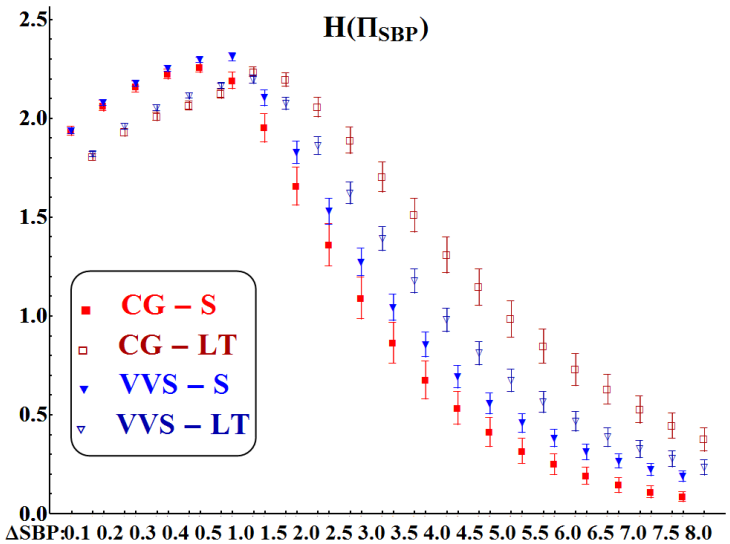

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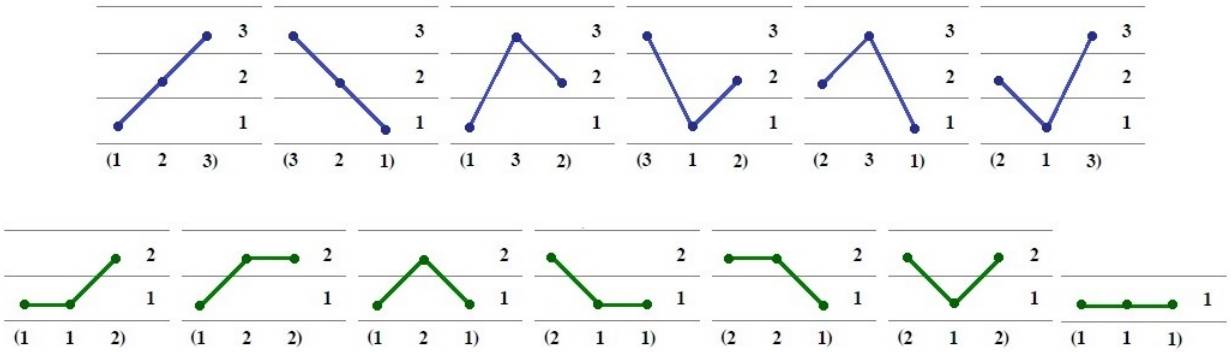

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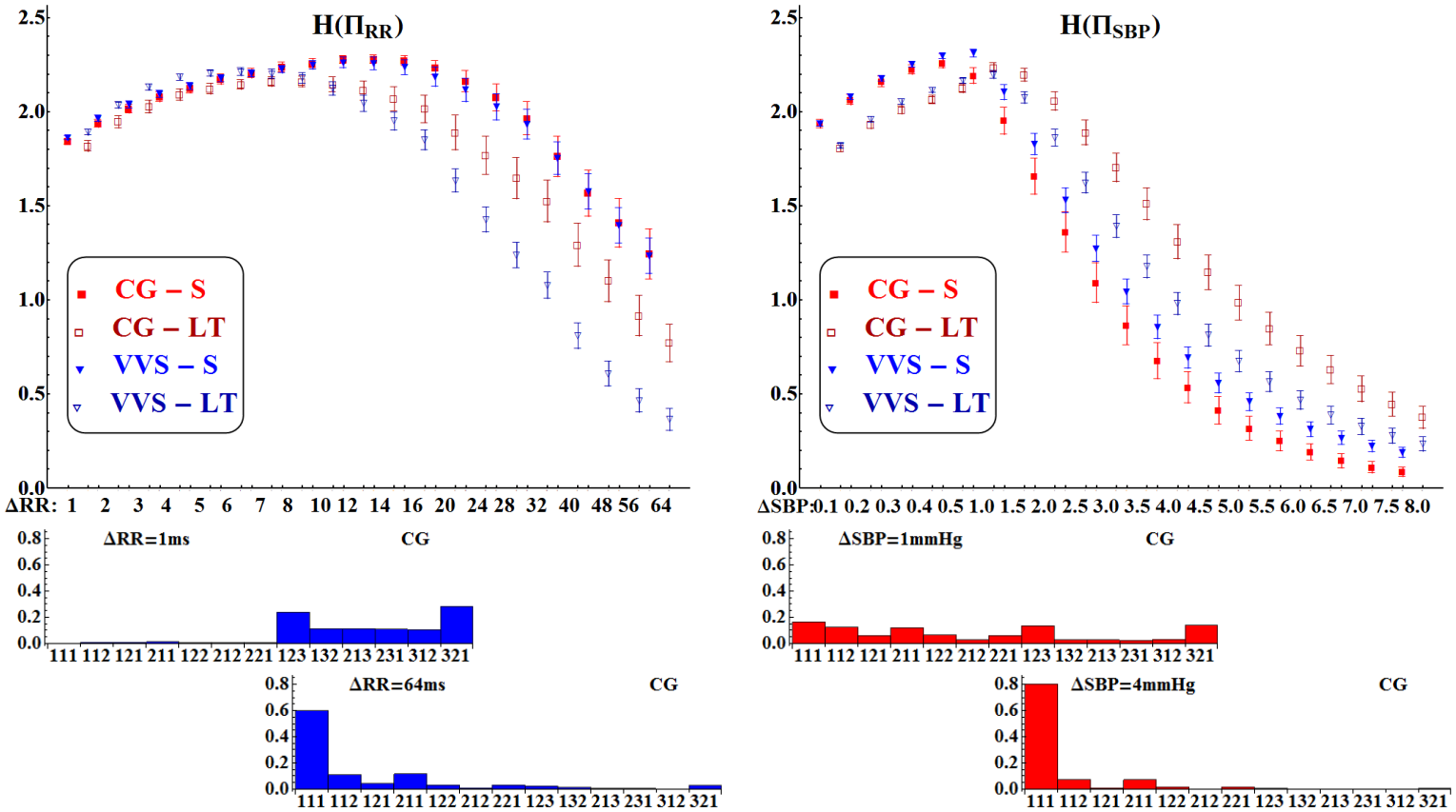

Cardiovascular interactions during head-up tilt test by transfer entropy between ordinal patterns of heart rate and blood pressure

Transfer entropy

X – driver process Y – target process

$$TE_{X\to Y} = \sum_{y_i, y_i^-, x_i^-} p(y_i, y_i^-, x_i^-) \log \frac{p(y_i|y_i^-, x_i^-)}{p(y_i|y_i^-)}$$

where:

- i – indicates a given point in time series,
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- Information about the number of significant realizations for a given link $X \to Y$ the method returns.

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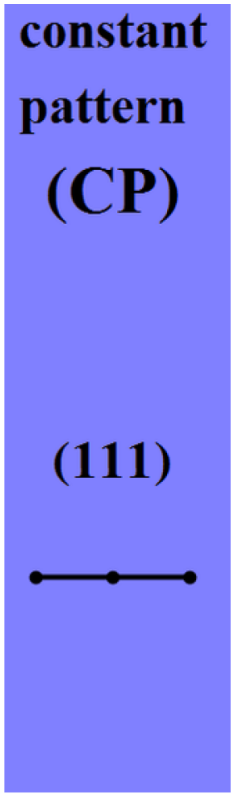

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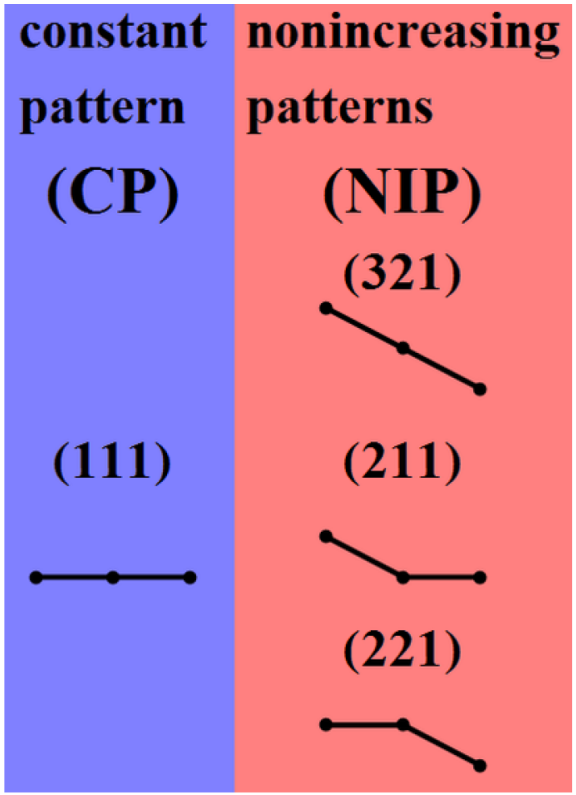

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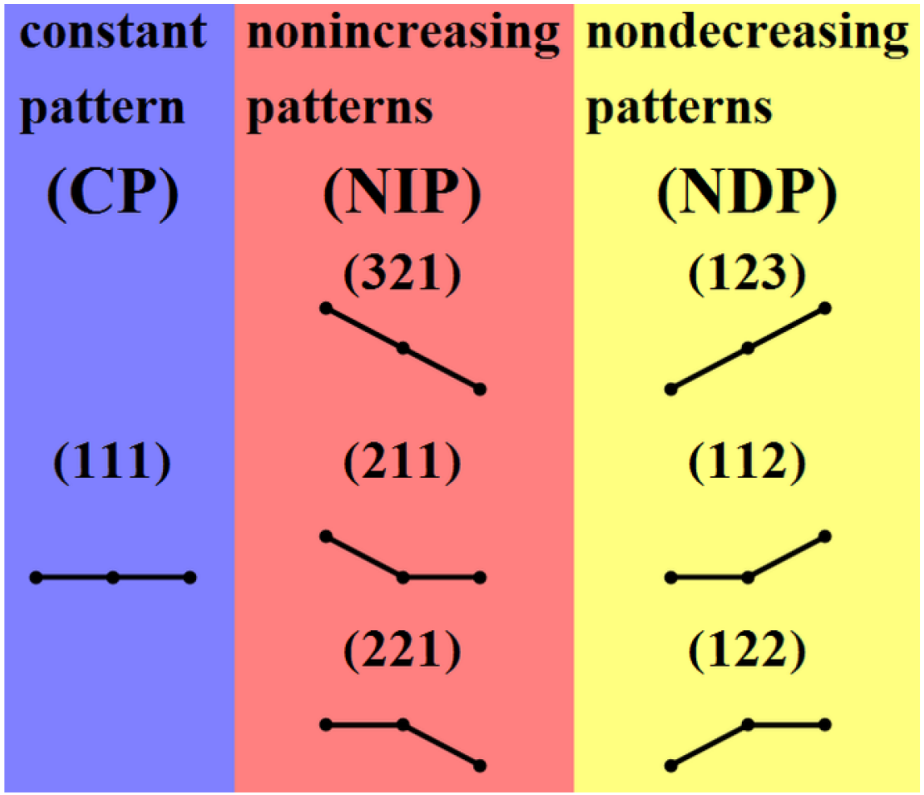

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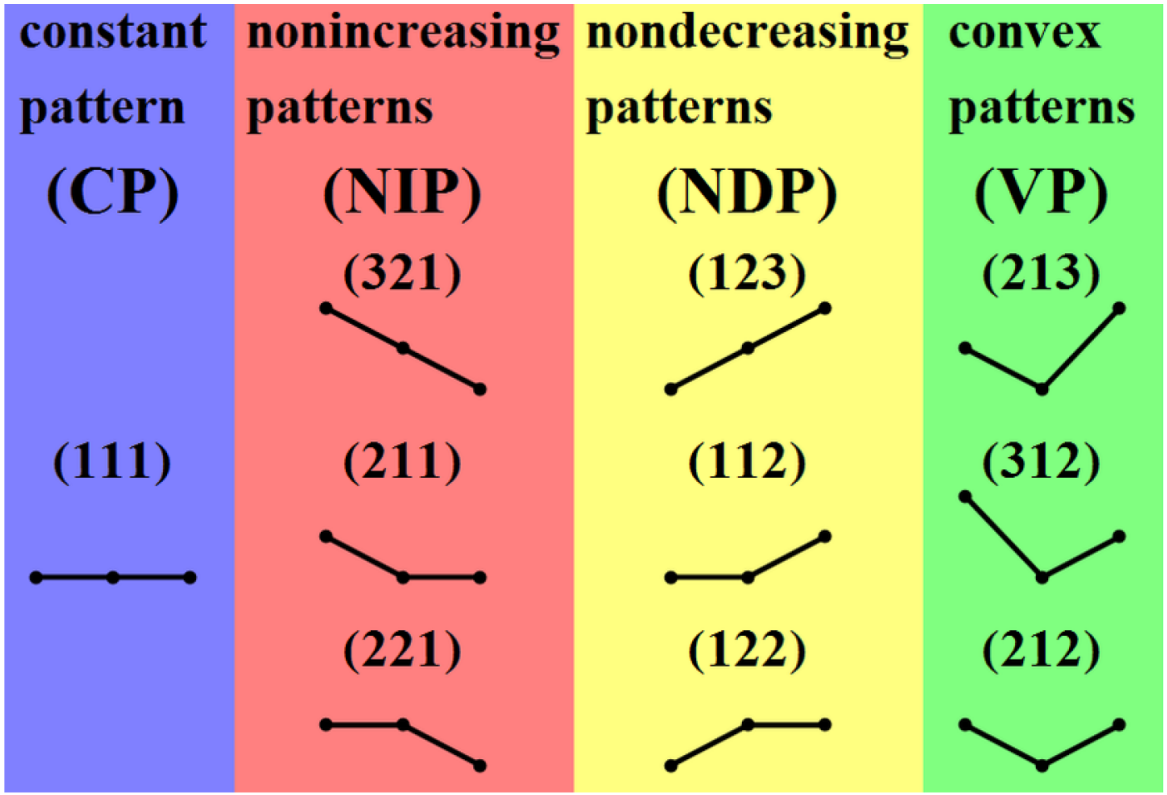

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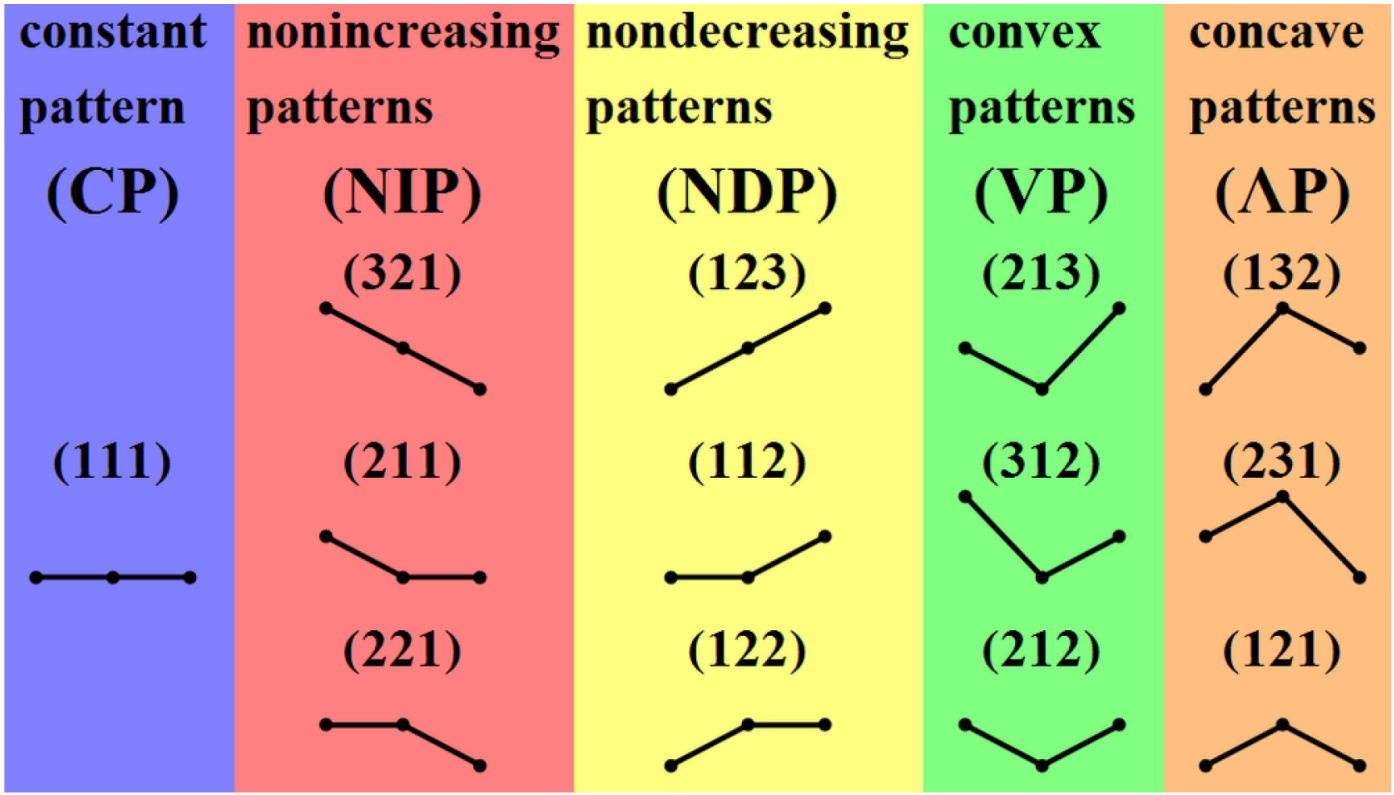

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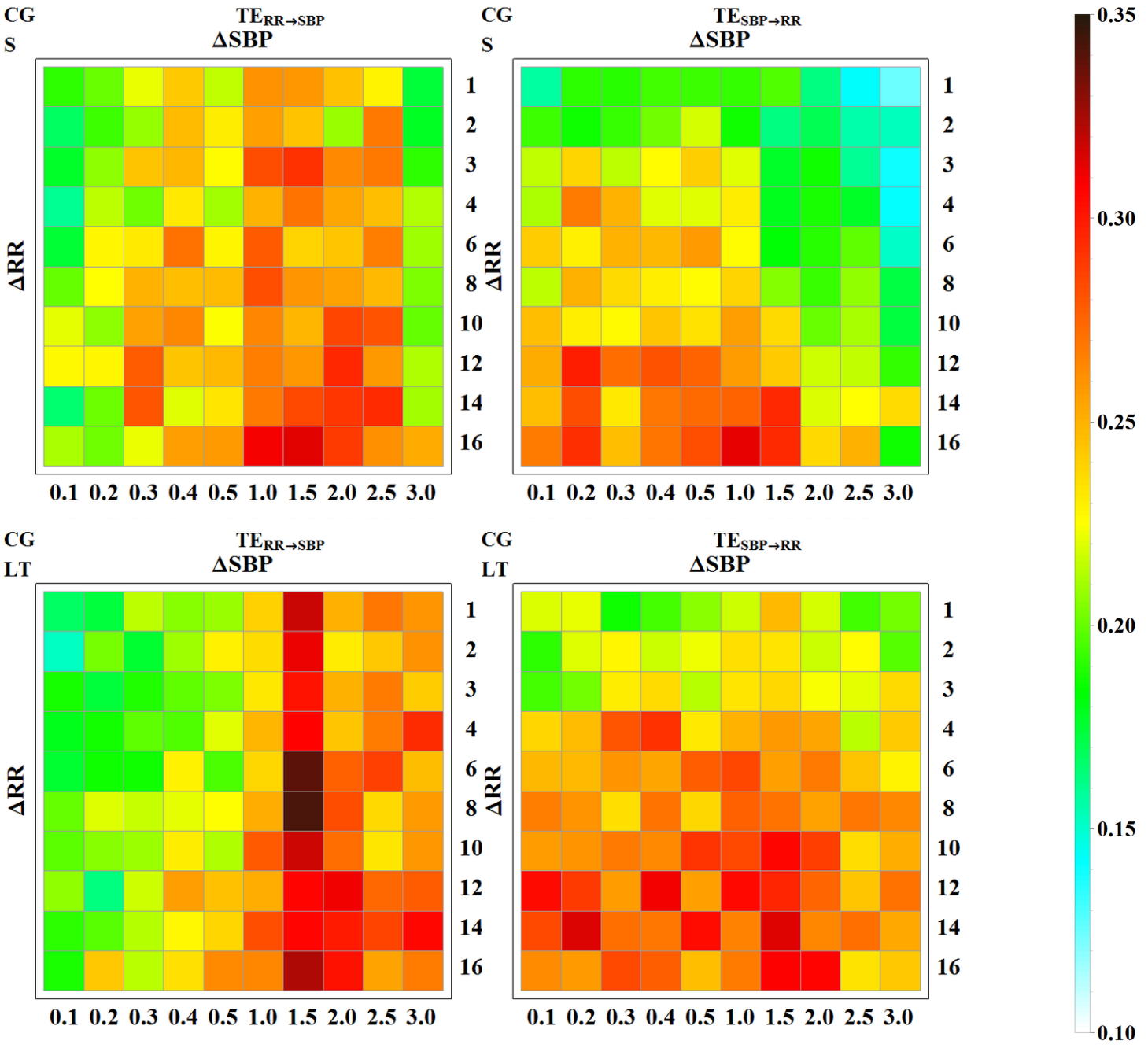

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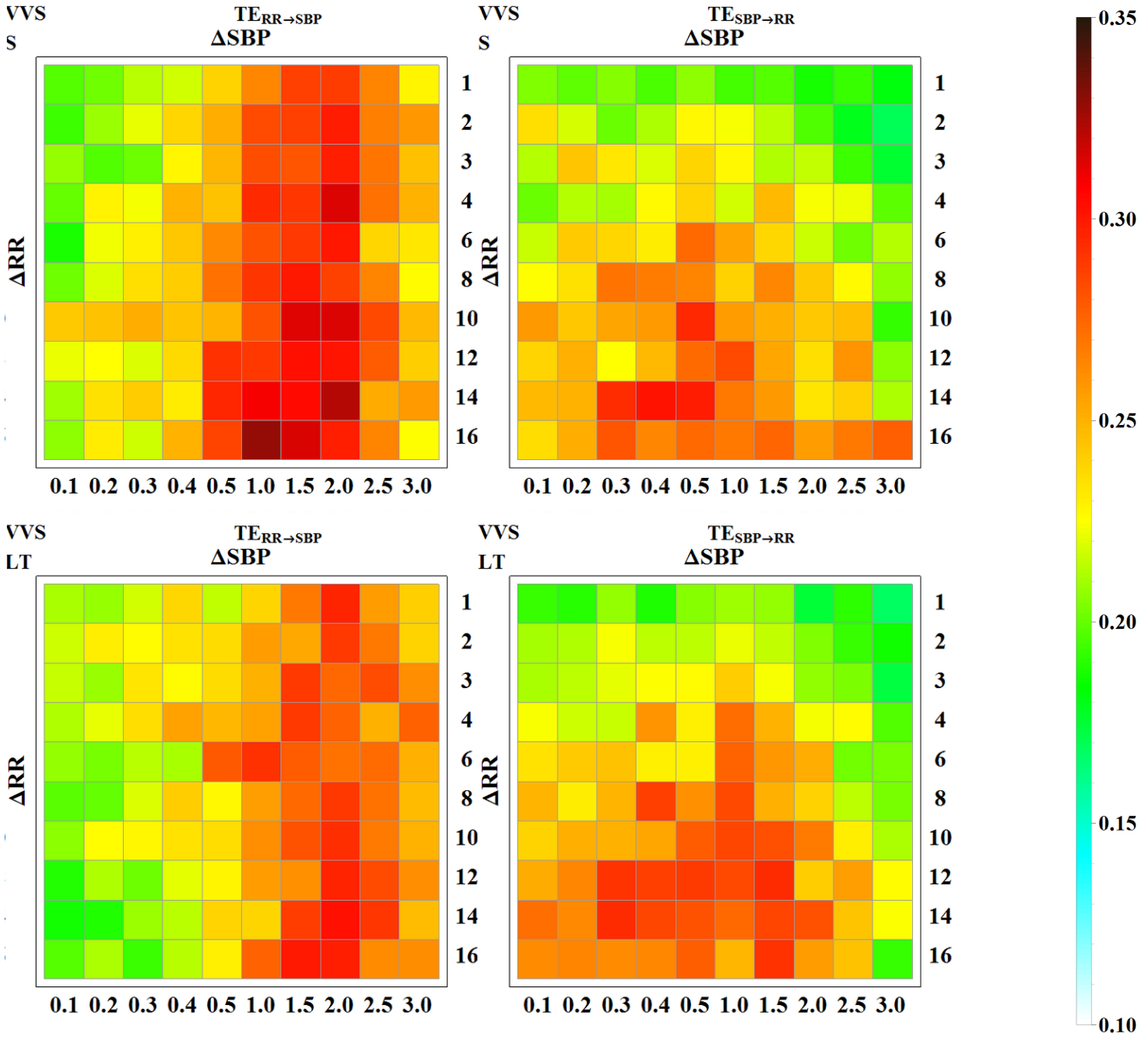

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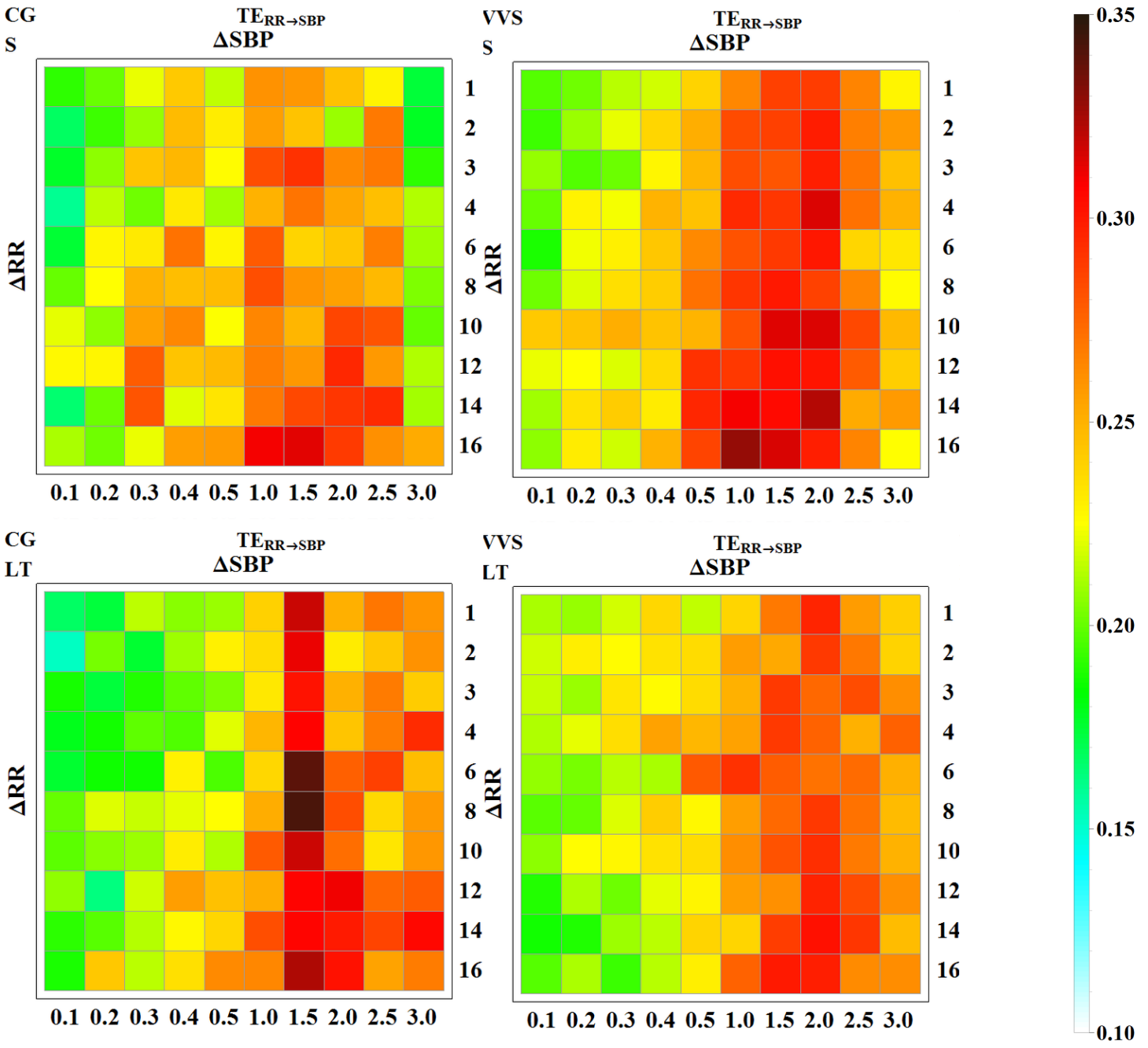

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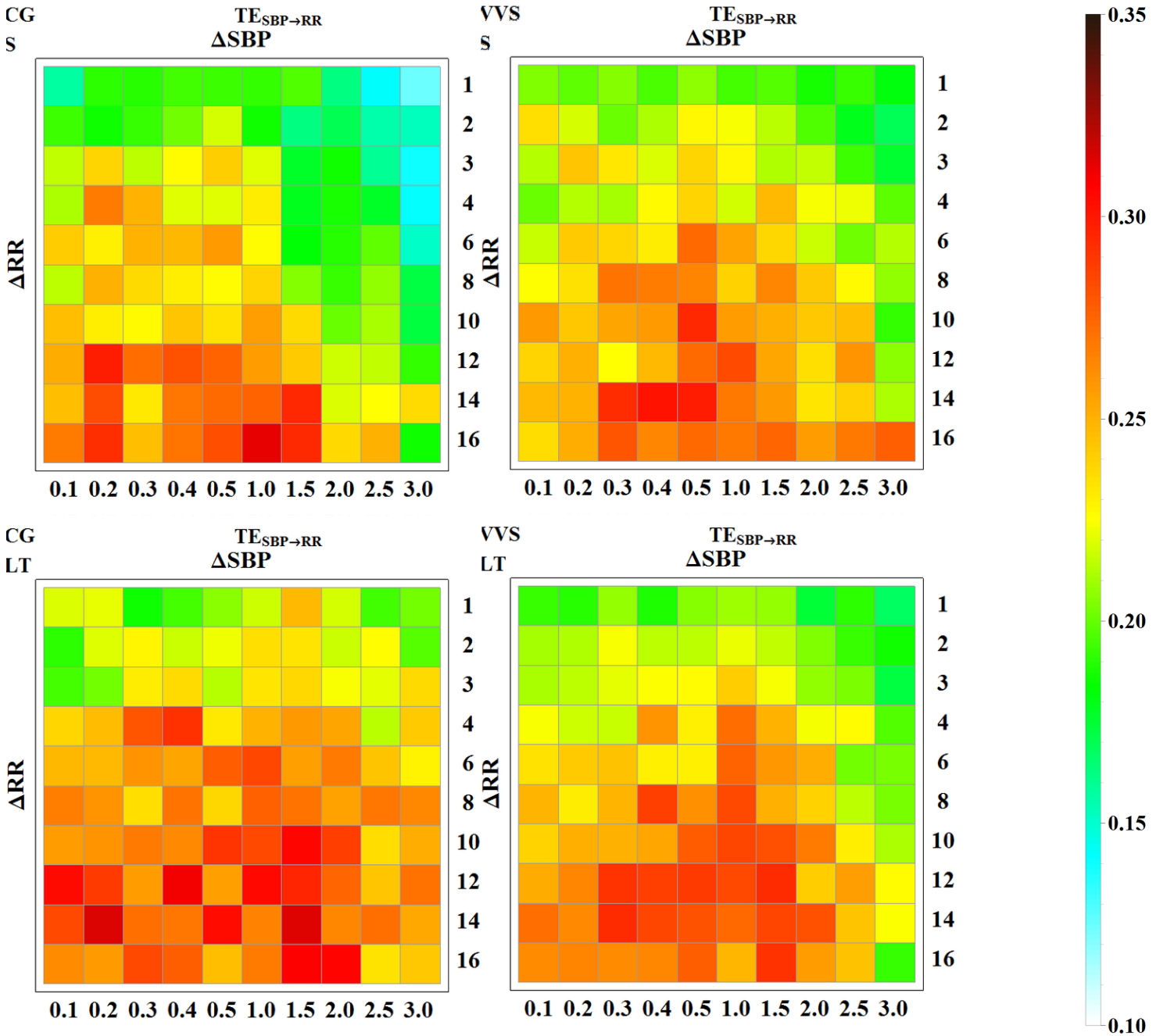

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- The transfer entropy between series representing RR-intervals and SBP values does not change significantly in case of vasovagal patients.
- Significant changes of $TE_{RR \to SBP}$ and $TE_{SBP \to RR}$ are obtained for healthy people during HUT test.
- Therefore our approach provides a way to observe the proper and improper interactions in cardiovascular system.

Thank you for your attention!

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