# Process Mining
# with
# Exogenous Data

Traditional Thesis by Monograph

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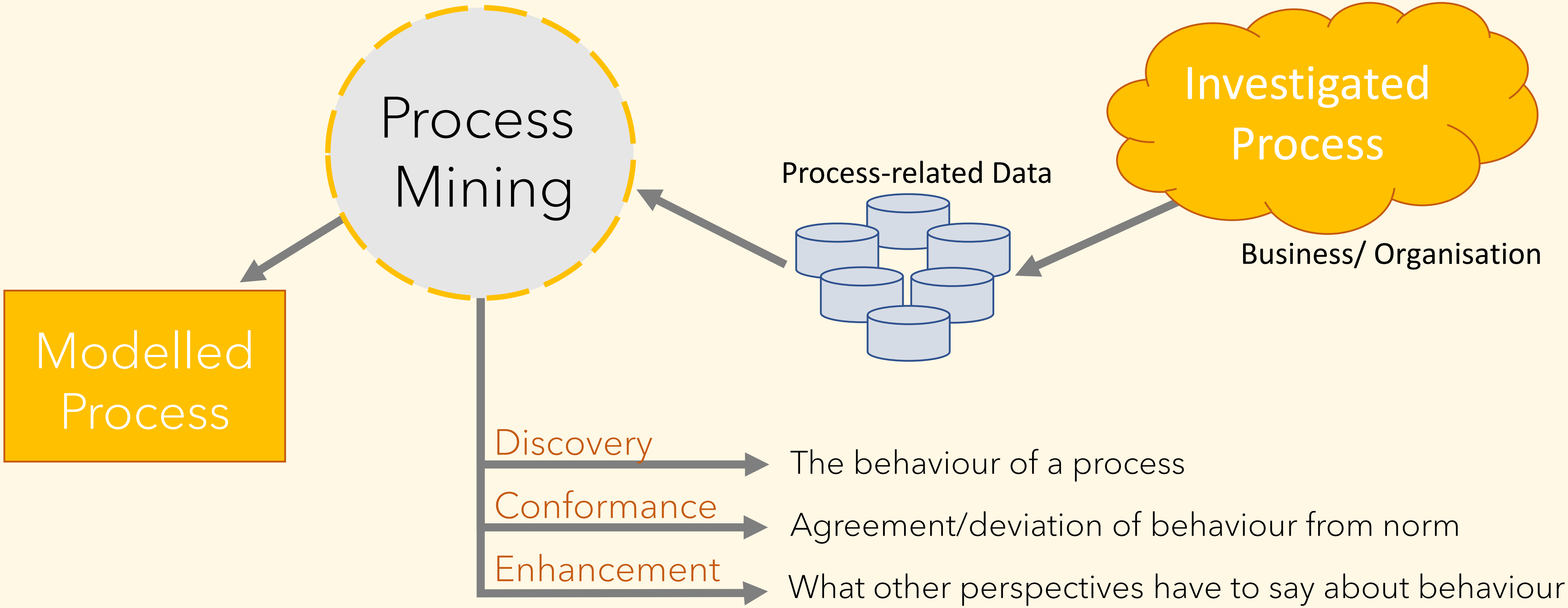
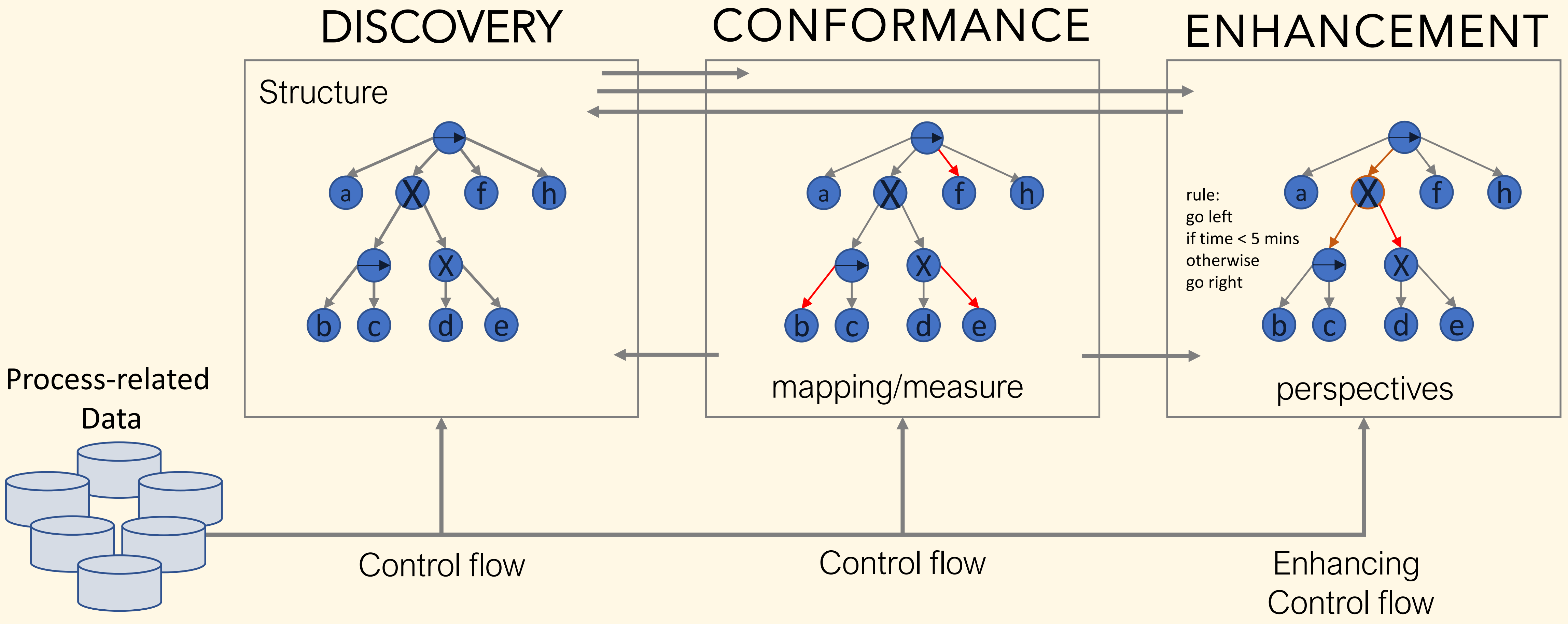
Principal: Prof Moe Thandar Wynn
Associate: Dr Robert Andrews
External: Prof Sander Leemans

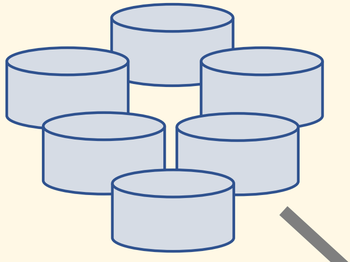
# Process Mining



# Process Mining



# Endogenous Data



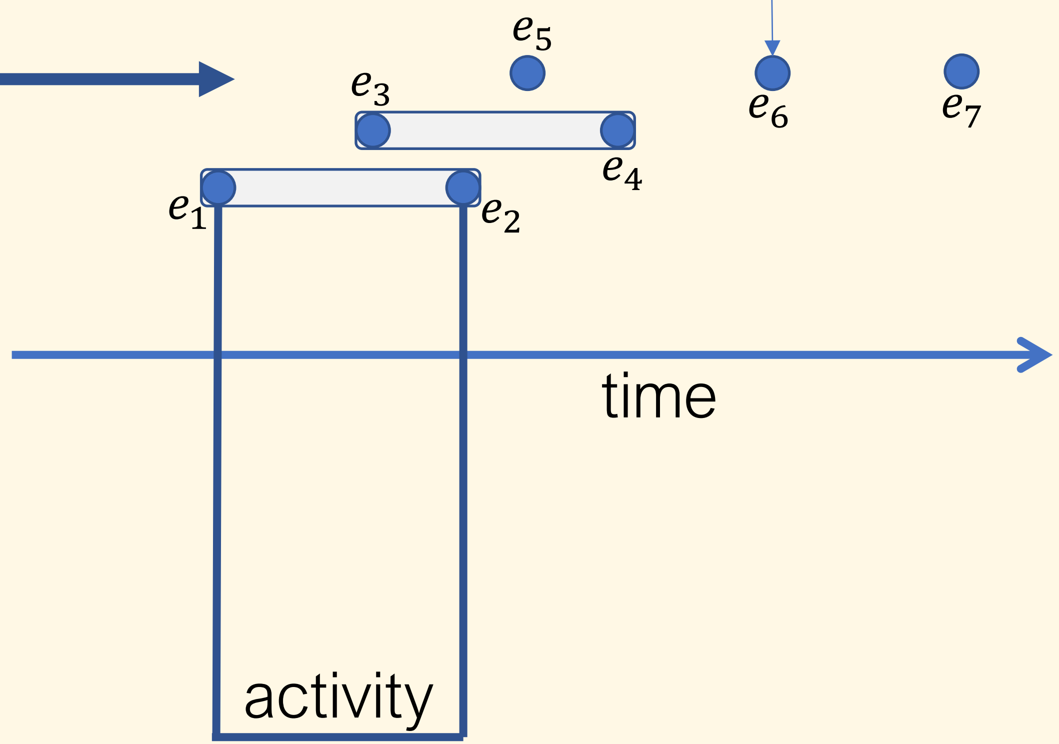
Process-related Data

Event log

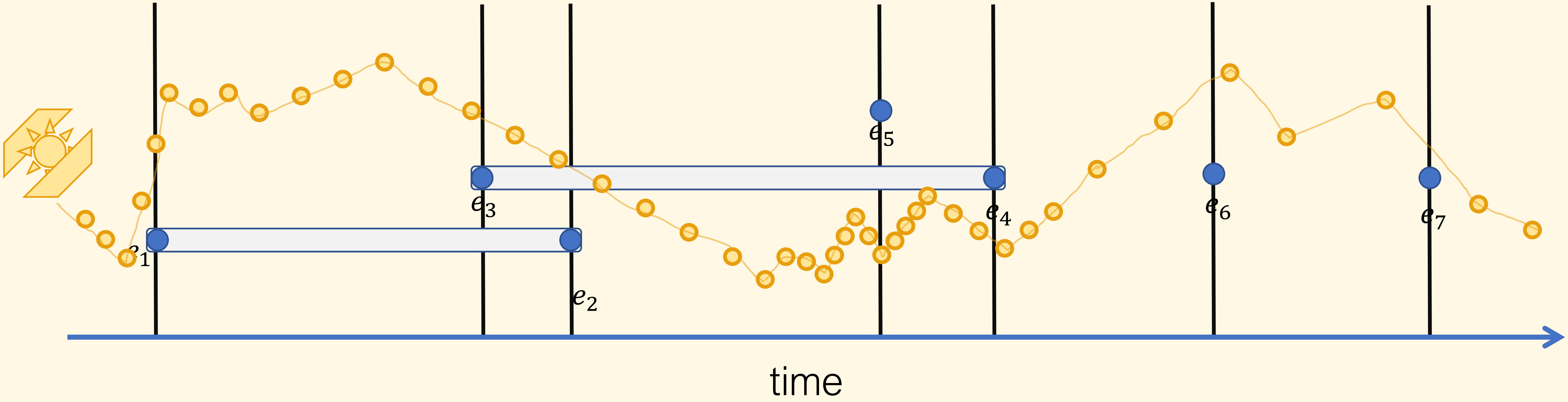
| case | act | res | cst | time | lyfc | $e_{\#}$ |
|---|---|---|---|---|---|---|
| Trace one | A | #13 | $40 | 04:00 | start | 1 |
| | A | #13 | | 04:30 | end | 2 |
| | B | #14 | $25 | 04:20 | start | 3 |
| | B | #13 | | 04:40 | end | 4 |
| | C | #15 | $12 | 04:50 | end | 5 |
| | D | #15 | $4 | 05:00 | end | 6 |
| | E | #16 | $2 | 05:15 | end | 7 |
| Trace two | A | #14 | $40 | 07:00 | start | 8 |
| | A | #14 | | 07:33 | end | 9 |
| | B | #14 | $25 | 07:28 | start | 10 |
| | B | #14 | $2 | 07:38 | end | 11 |
| | C | #15 | $12 | 07:40 | start | 12 |
| | C | #15 | | 07:59 | end | 13 |
| | E | #16 | $2 | 08:15 | end | 14 |

{ activity: D,
time: 05:00,
resource: #15,
cost: $4,
lifecycle: end }

even



# Exogenous Data



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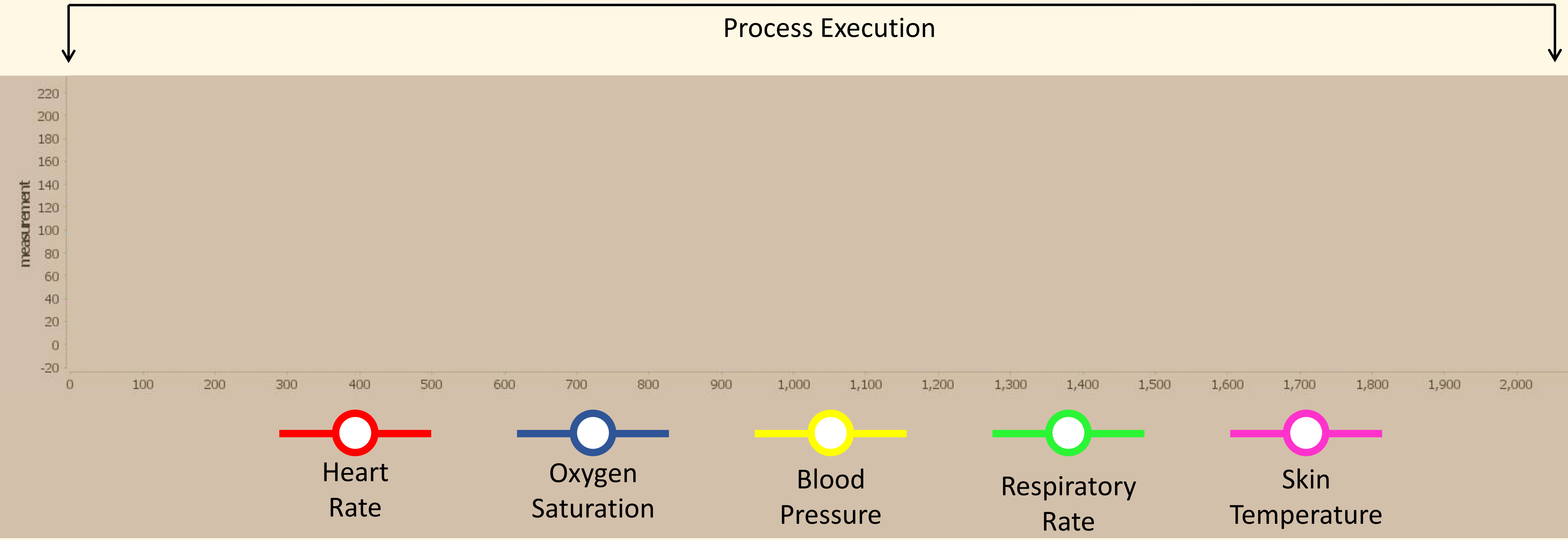


# Research Gaps

*Only event attributes are considered…*

- Data Source types around processes: Roseman et al (2008) [1] & van der Aalst and Dustdar (2012) [2]
- Intra/inter-trace attributes: Senderovich et al (2019) [3]
- Intra trace temporal attributes: Pourbafrani et al (2021) [4]
- Contextual events: Dees et al (2020) [5]
- Mutli-level processes based on event attributes: Leemans et al (2020) [6]
- Data expression restrictions on behaviour: Shraga et al (2019) [7]
- Challenges for process mining adoption: Munoz-Gama et al (2021) et al [8]

*Process-decision rules only consider logical operators consisting of {=,≠,<,>}*
*No temporal operators…*

- Decision Miner: Rozinat (thesis) (2010) [9]
- Alignment based Decision Miner: De Leoni and van der Aalst (2013) [10]
- Linear equalities with multiple variables for decision expressions: De Leoni et al (2013) [11]
- Non-exclusive decision mining: Mannhardt et al (2016) [12]
- Conformance measures to correct for decision expressions: Mannhardt (thesis) (2018) [13]
- Variable to variable expressions (read/written): Felli et al (2019) [14]

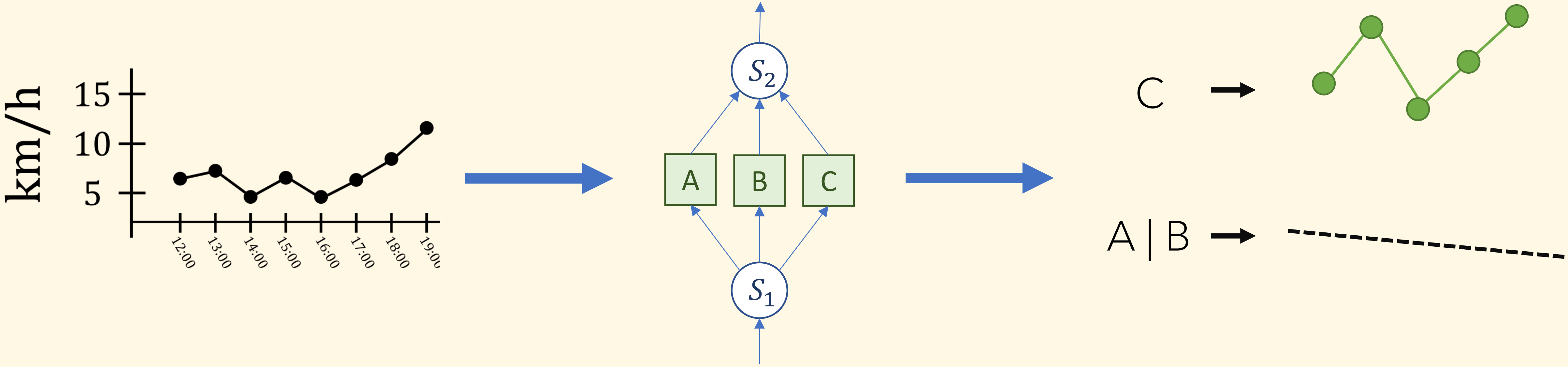
*No studies were found that focus on the temporal changes of decision-making…*

- Global decision making: Winter and Rinderle-Ma (2017) [15] and Winter et al (2020) [16]
- Declarative constraints: Pesic et al (2007) [17] and Leno et al (2020) [18]
- Temporal changes to intermediately available data: van Zelst (thesis) (2019) [19]
- Temporal changes to structure of process behaviour: Stertz et al (2020) [20] and Brockhoff et al (2020) [21]
- High velocity of events requiring abstractions: Mannhardt et al (2018) [22] and Smedt et al (2021) [23]

# Process Mining
## with
# Exogenous Data

*Research Aim*

*How can analysts study the influence of exogenous data on decisions in processes?*



# Process Mining
## with
# Exogenous Data

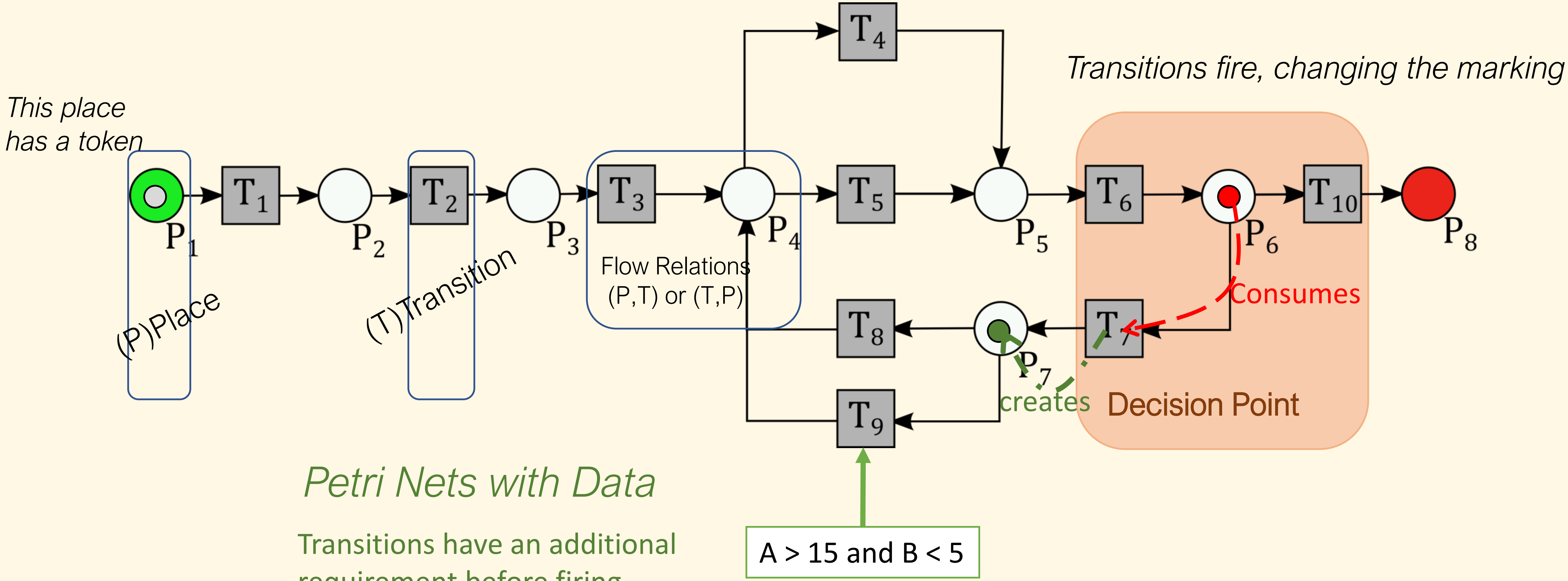
*Research Questions*

*How can we represent and use exogenous data in existing process mining techniques?*

*How can patterns/artefacts in exogenous data be identified and represented for decision-making?*

*How can analysts study the influence of exogenous data on decision-making variance in processes?*

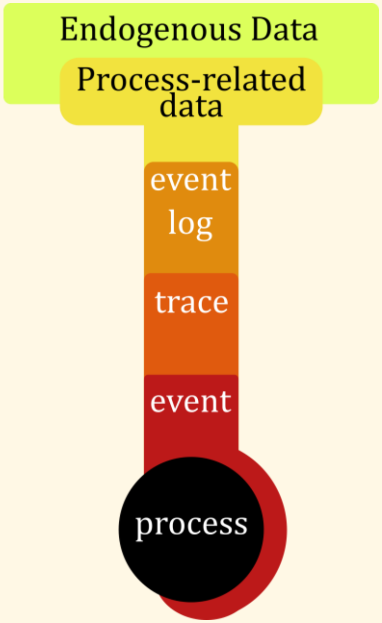
# Petri Nets

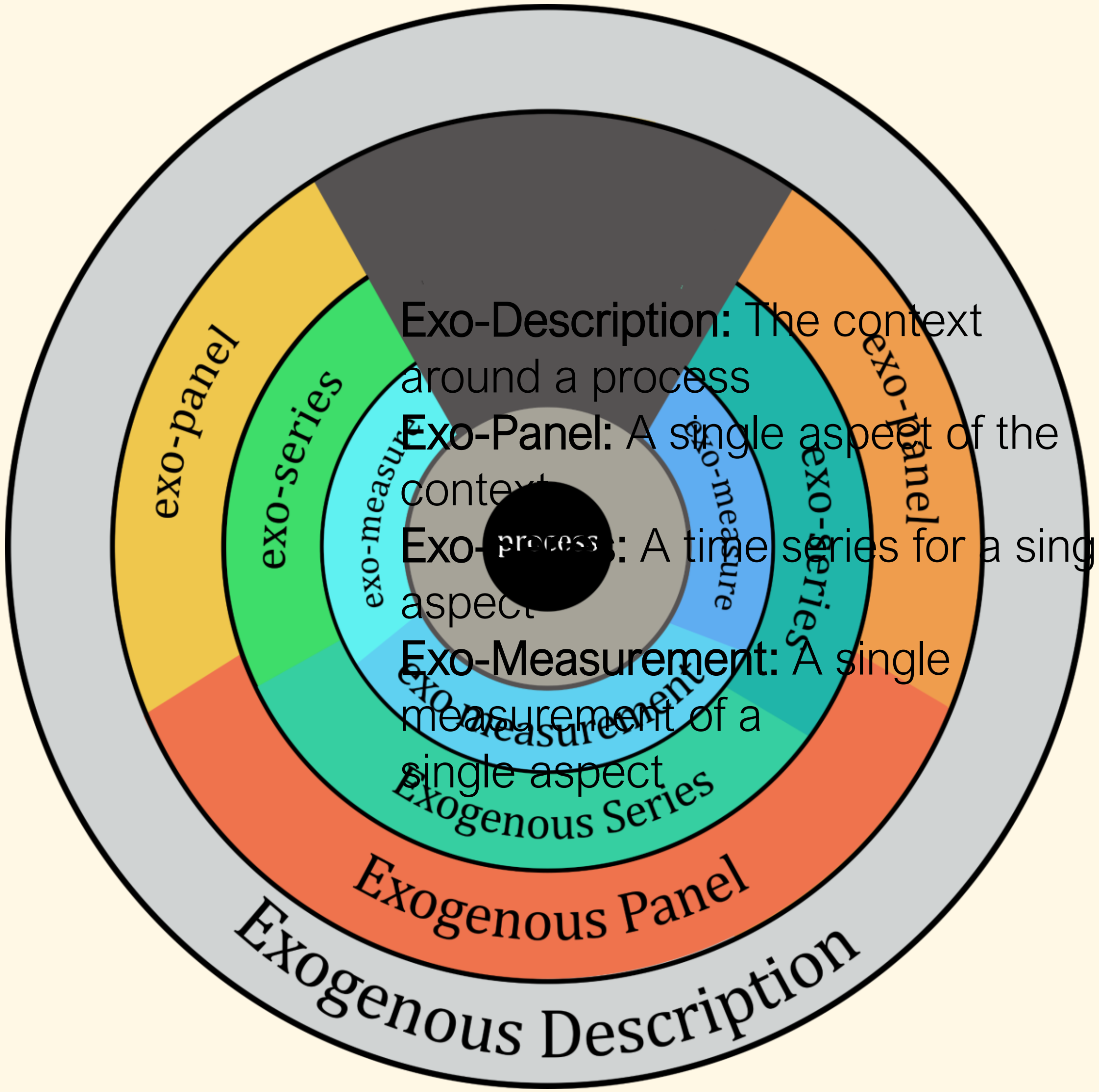



*Petri Nets with Data*

Transitions have an additional requirement before firing...

# Exogenous Data




**Exo-Description:** The context around a process

**Exo-Panel:** A single aspect of the context

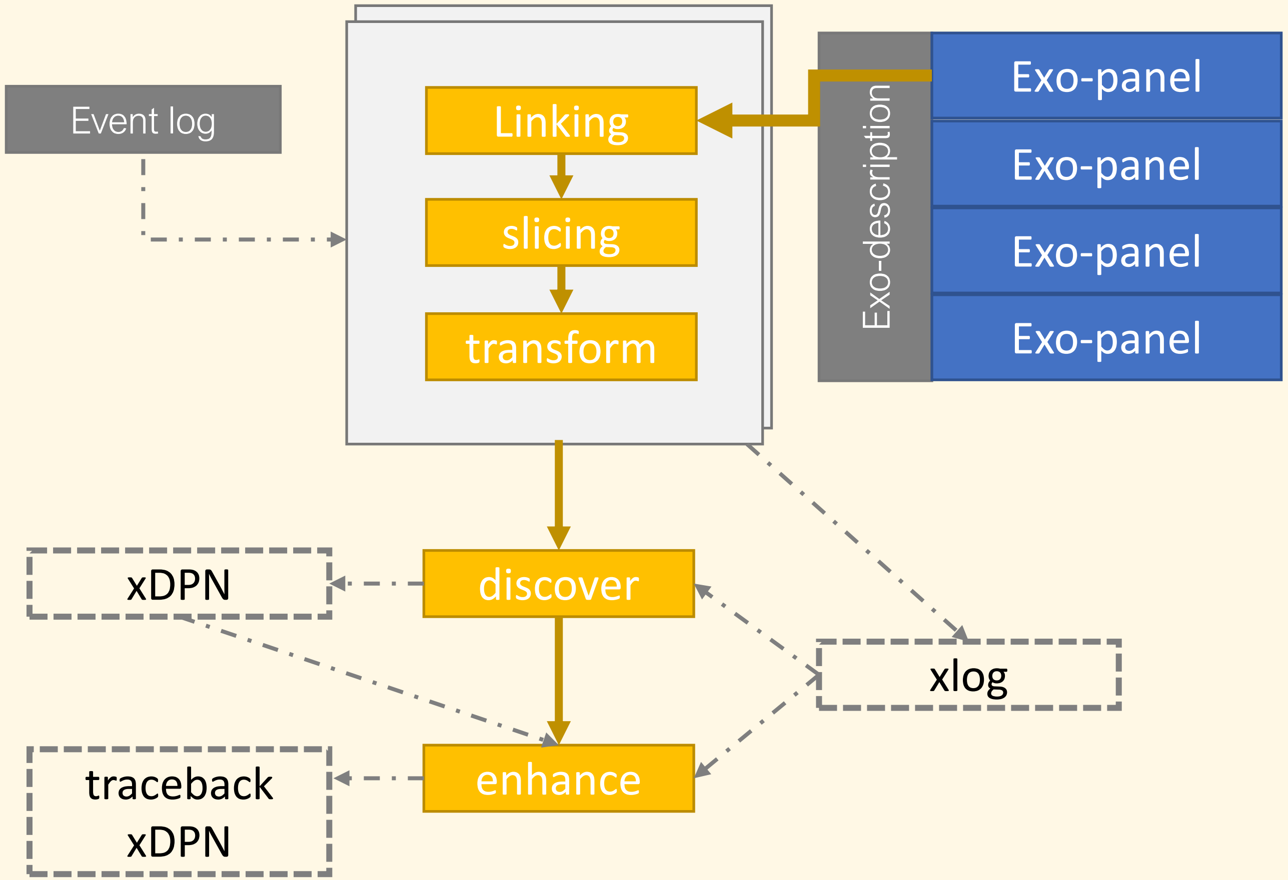
**Exo-Series:** A time series for a single aspect

**Exo-Measurement:** A single measurement of a single aspect

# Exogenous Data

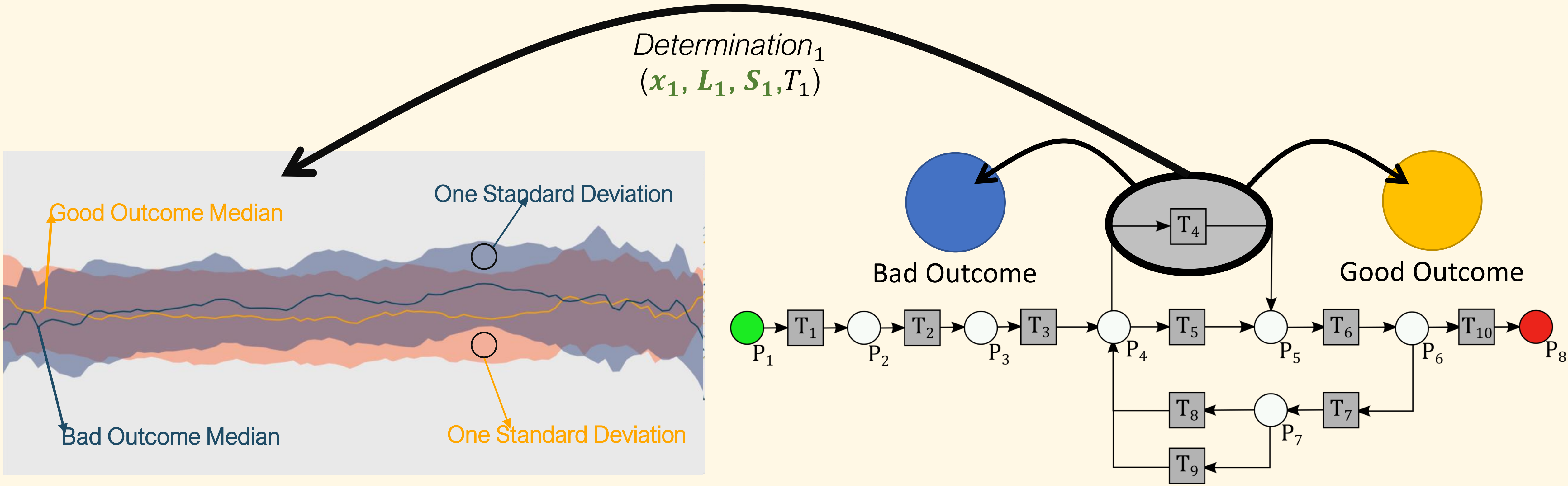
*RQ ONE*
*How can we represent and use exogenous data in existing process mining techniques?*

# xPM
# Framework for process mining with exogenous data




- By applying several *determinations*, we describe the possible influences affecting process behaviour
- *Determinations* are tuples of (**x, L, S, T**), consisting of:
  - an exogenous data source (exo–panel or **x**),
  - a linking function to connect a trace and an data source, to find a time series (exo-series or **L**),
  - a slicing function to create a subset of an exo–series (*slice*) for an event (**S**),
  - a transformation function to create transformed attributes for an event (**T**).

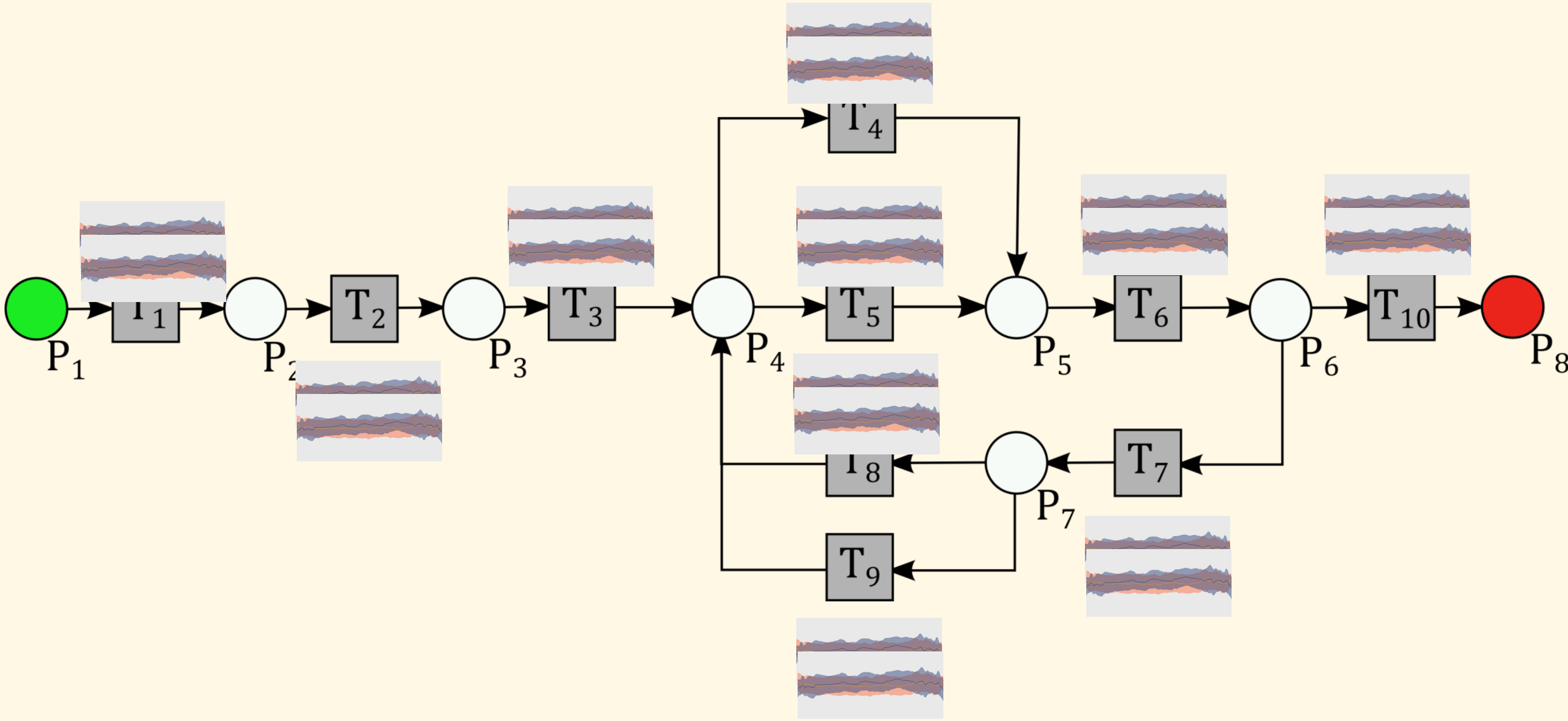
# Explorative Exogenous Series Analysis (EESA)



# Ranking a Collection of EESAs

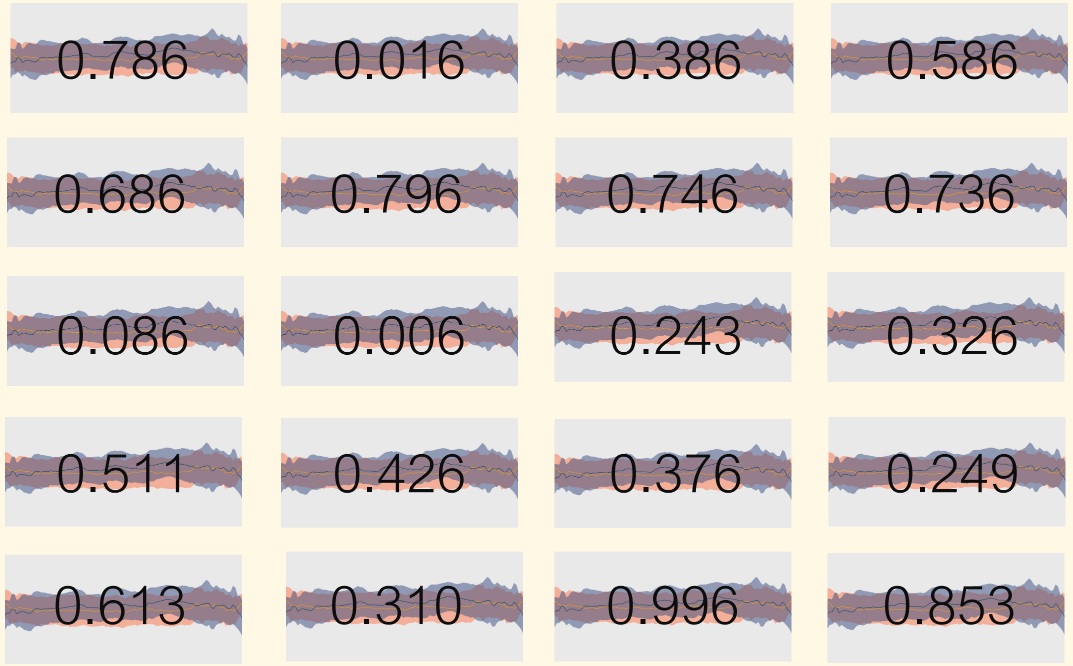
*Determination*$_1$ $(\boldsymbol{x_1}, \boldsymbol{L_1}, \boldsymbol{S_1}, T_1)$

*Determination*$_2$ $(\boldsymbol{x_2}, \boldsymbol{L_2}, \boldsymbol{S_1}, T_1)$



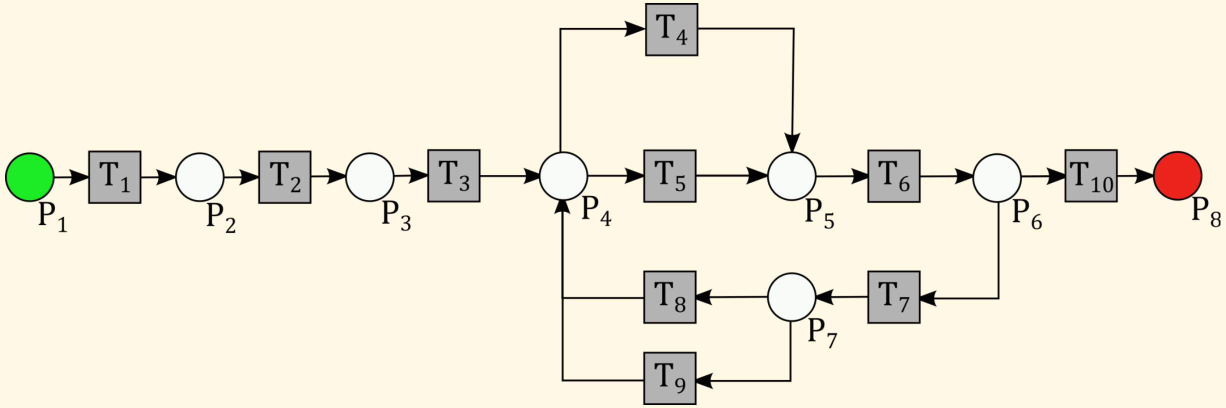
# Ranking a Collection of EESAs

Applying Dynamic Time Warping between
median trend lines for outcomes



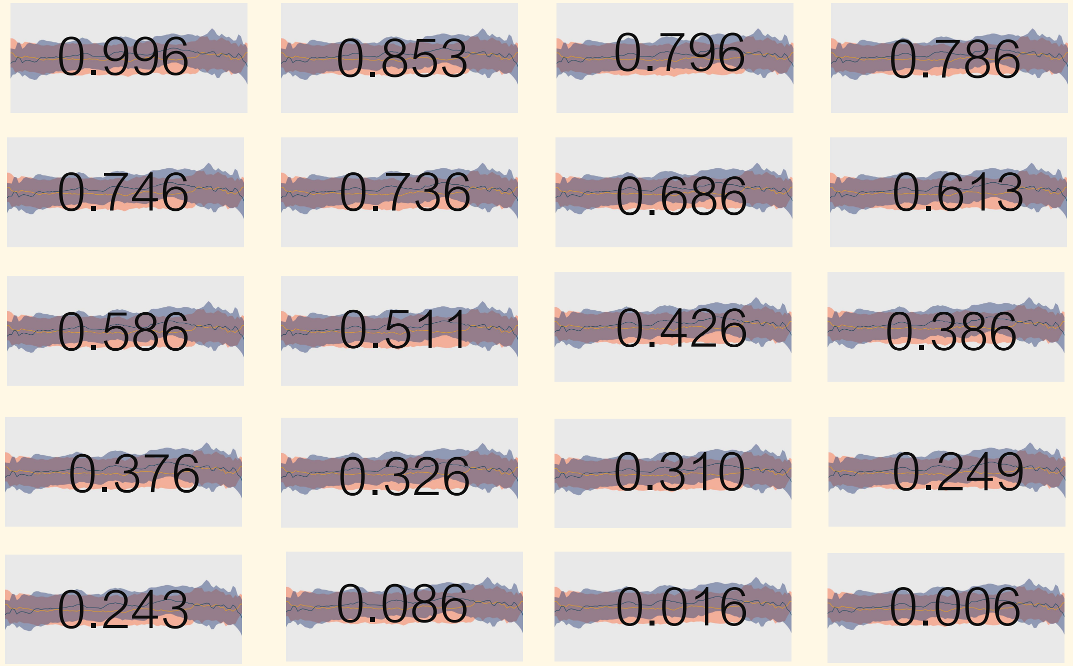

*Determination*$_1$
$(x_1, L_1, S_1, T_1)$

*Determination*$_2$
$(x_2, L_2, S_1, T_1)$



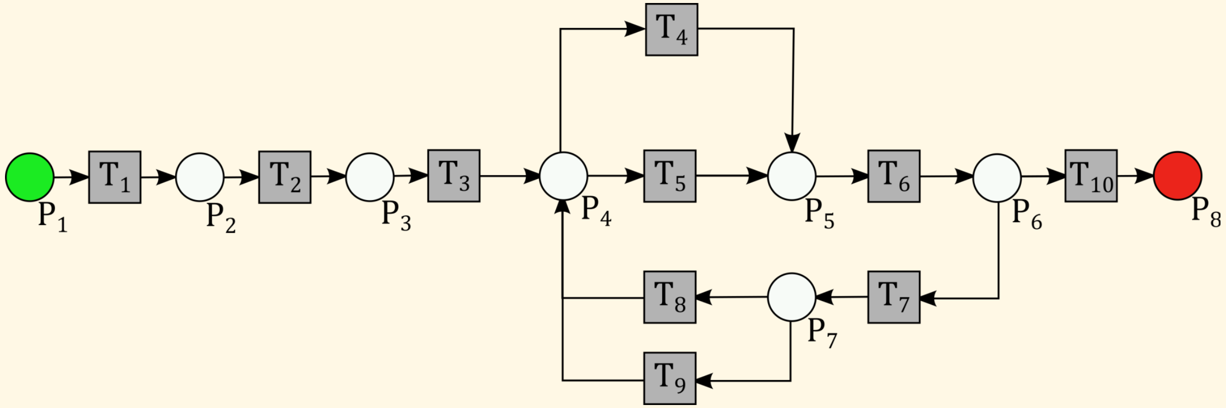
# Ranking a Collection of EESAs

Then we sort by descending value,
and an assign a rank




*Determination*$_1$ $(\boldsymbol{x_1}, \boldsymbol{L_1}, \boldsymbol{S_1}, T_1)$

*Determination*$_2$ $(\boldsymbol{x_2}, \boldsymbol{L_2}, \boldsymbol{S_1}, T_1)$



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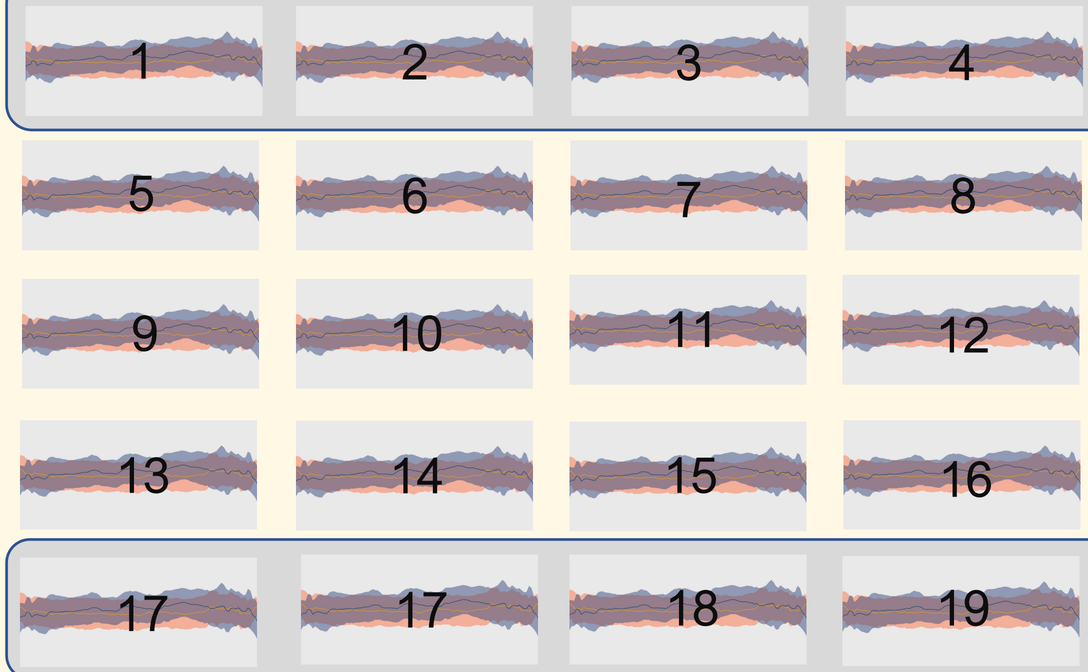
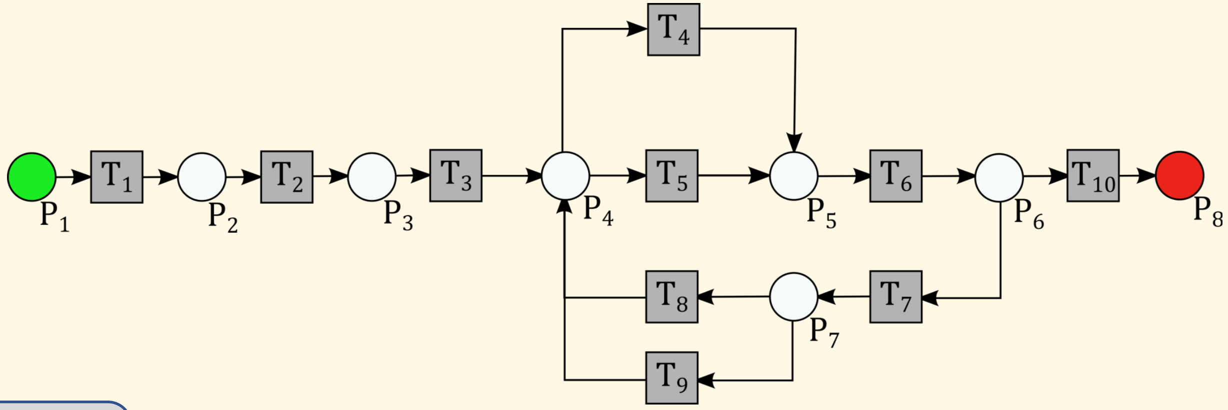



most different

most similar

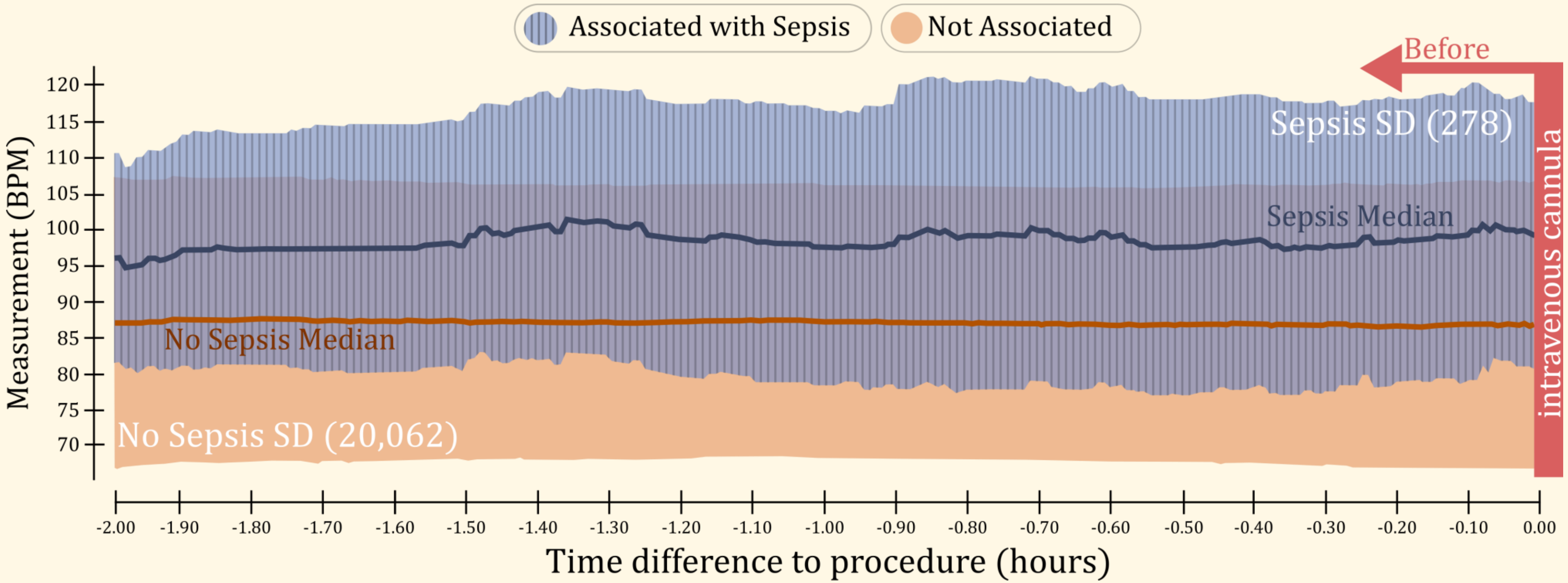
*Determination*$_1$ $(\boldsymbol{x_1}, \boldsymbol{L_1}, \boldsymbol{S_1}, T_1)$

*Determination*$_2$ $(\boldsymbol{x_2}, \boldsymbol{L_2}, \boldsymbol{S_1}, T_1)$

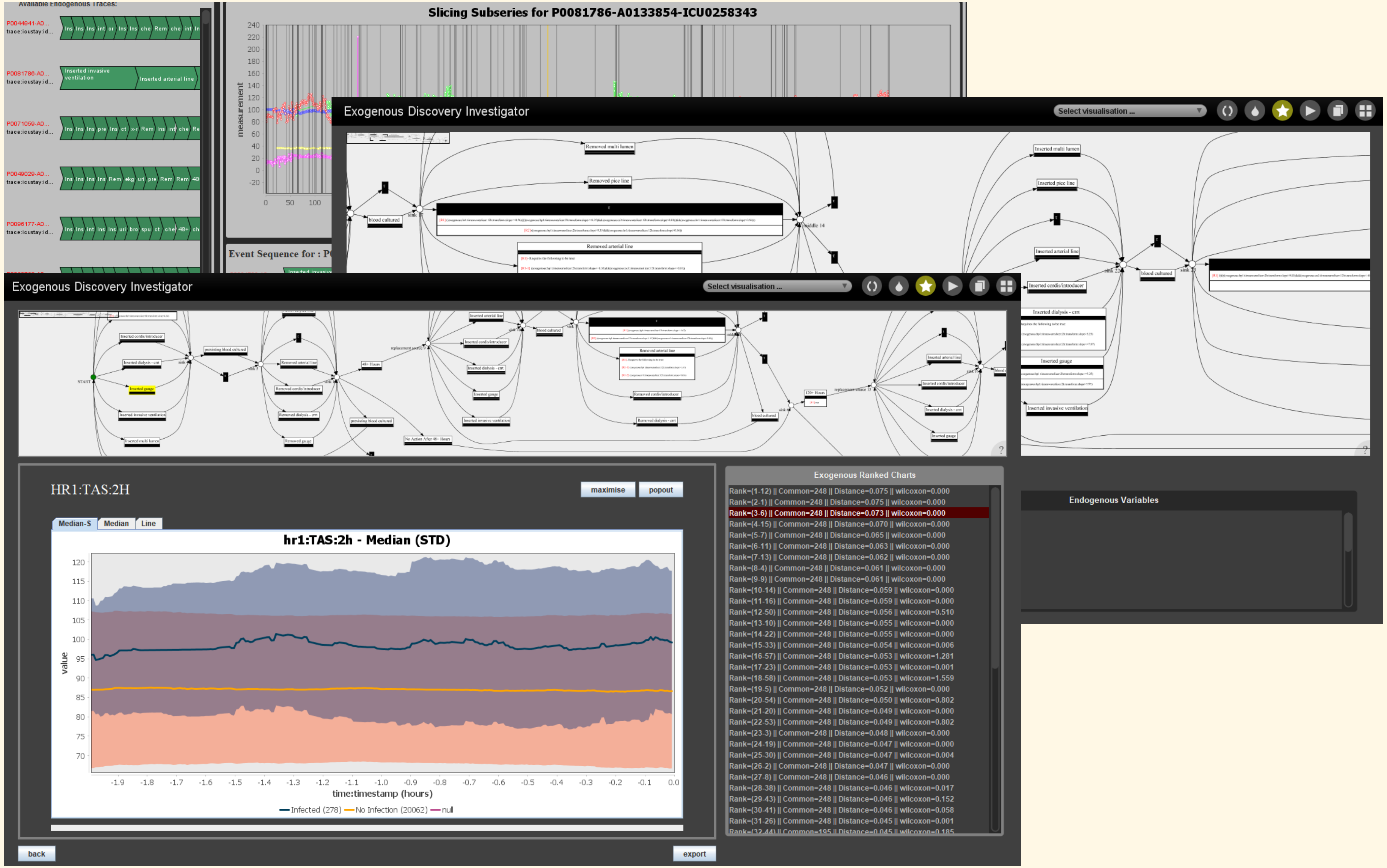


# xPM for Healthcare

- Used the publicly available dataset, MIMIC-III [27]
- Published workshop paper [26], at Event Data and Behaviour Analysis workshop, co-located at ICPM2021
- Worked with healthcare domain experts to investigate:
    - *Recognising patients with early or incubating infections and/or predicting those who will develop subsequent infections/sepsis*.
- Submission to special issue for the Journal of Artificial Intelligence for Medicine (Q1)



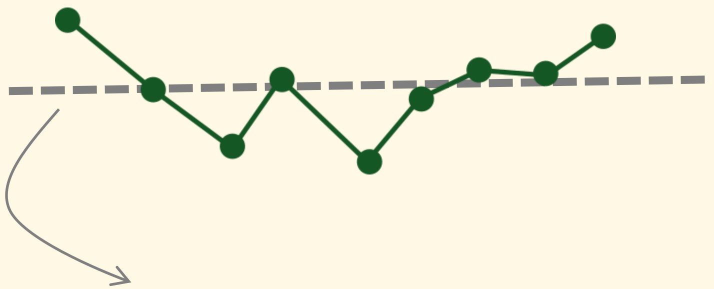
# Tool Support



# Patterns & Artefacts

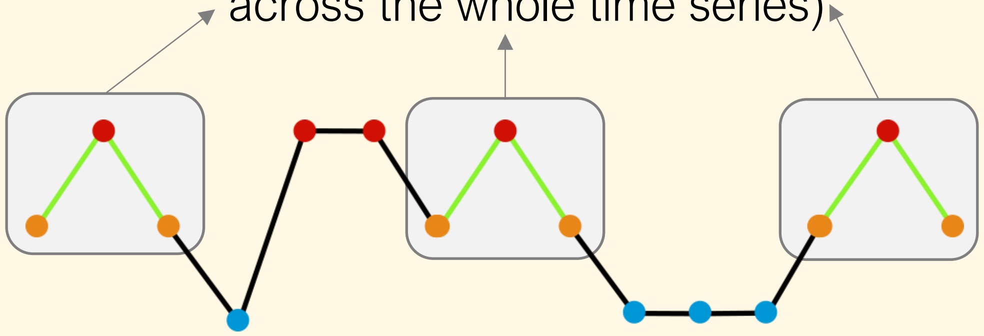
*RQ TWO*

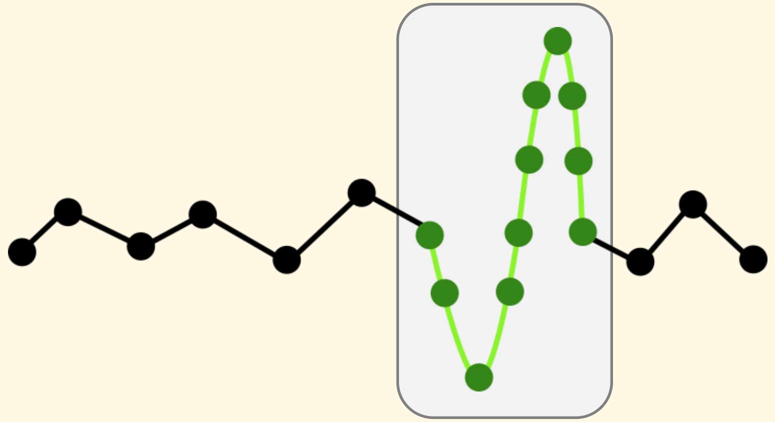
*How can patterns/artefacts in exogenous data be identified and represented for decision-making?*



Long running trends

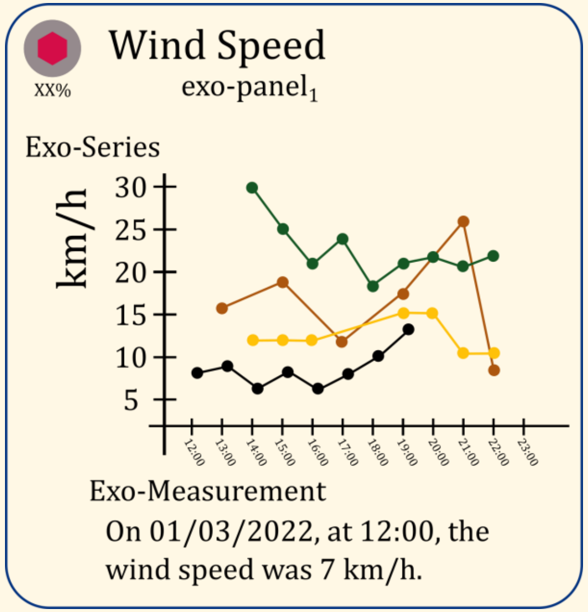
Patterns
(presented in many values across the whole time series)

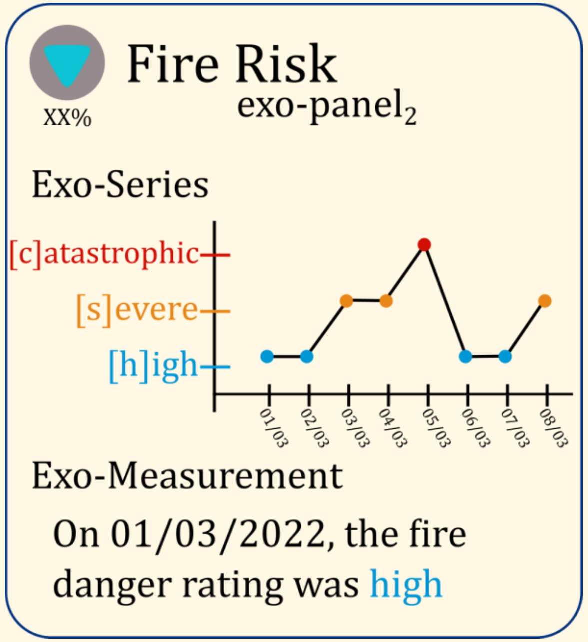


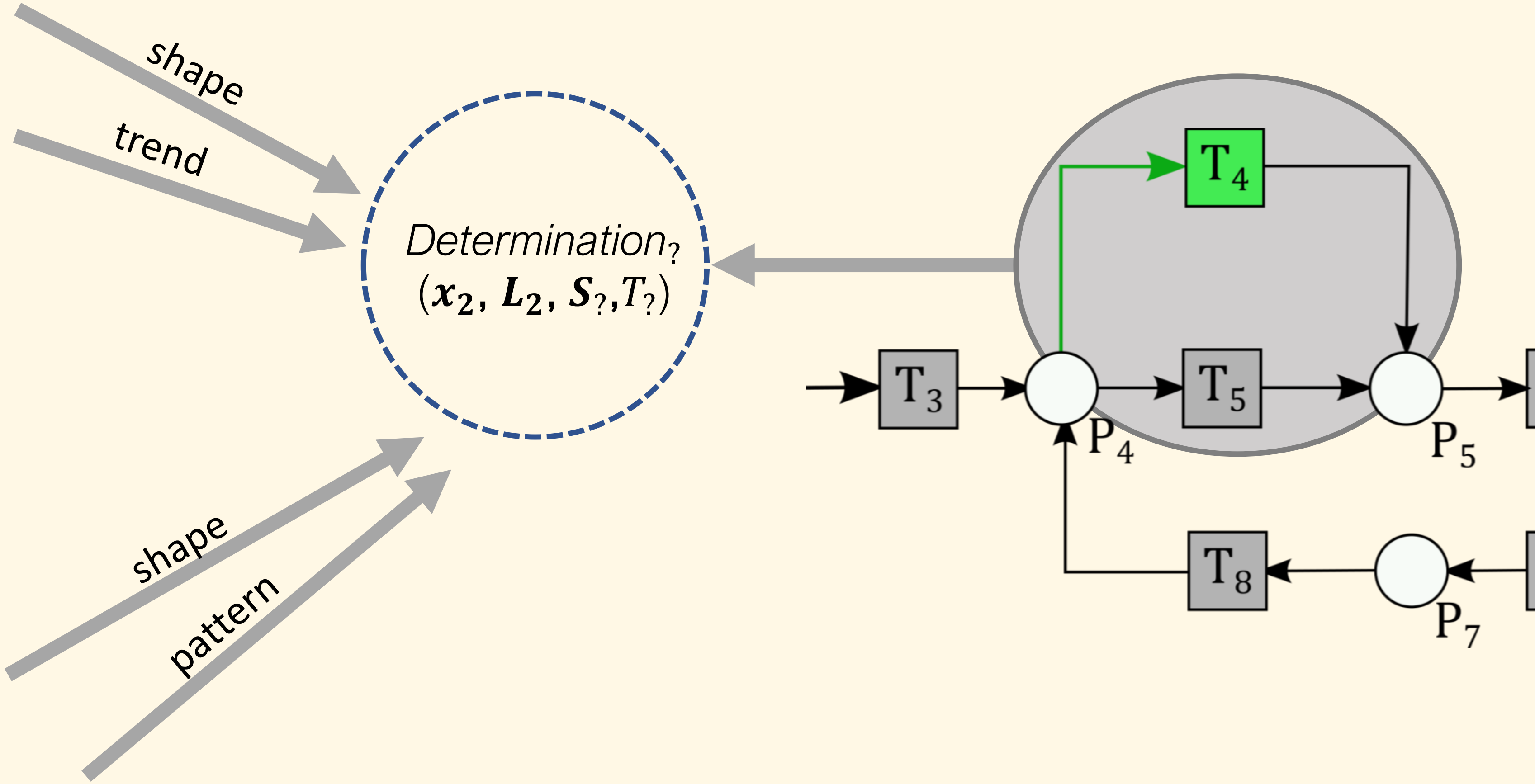


Shape
(presented in a unbroken sequence of values)

# Problem

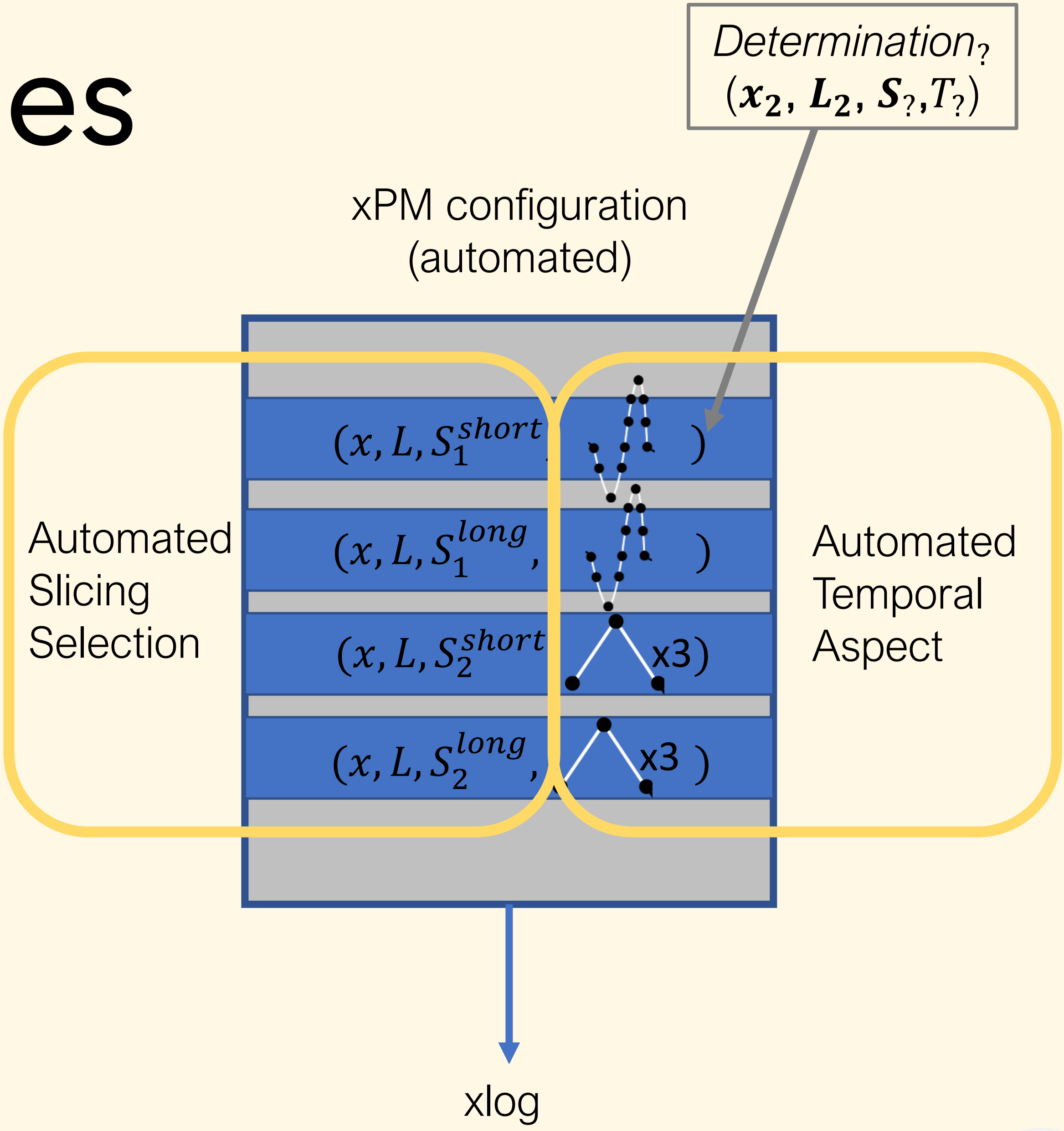

Wind Speed
XX%
exo-panel1
Exo-Series
km/h
30
25
20
15
10
5
12:00
13:00
14:00
15:00
16:00
17:00
18:00
19:00
20:00
21:00
22:00
23:00
Exo-Measurement
On 01/03/2022, at 12:00, the wind speed was 7 km/h.


Fire Risk
XX%
exo-panel2
Exo-Series
[c]atastrophic
[s]evere
[h]igh
01/03
02/03
03/03
04/03
05/03
06/03
07/03
08/03
Exo-Measurement
On 01/03/2022, the fire danger rating was high


shape
trend
shape
pattern
Determination?
(x2, L2, S?, T?)
T3
T4
T5
T8
P4
P5
P7

# Planned Outcomes

- Automated analysis of finding process-relevant determinations
  - For transforms functions with guarantees
    - a shape operator
    - a sequential/pattern operator
    - a trend operator
  - For slicing functions with guarantees
    - uses the least amount of data [just in time detection]
    - uses the most amount of data [early detection]
- Automatic construction of an xPM configuration.



# Decision-Making Variance

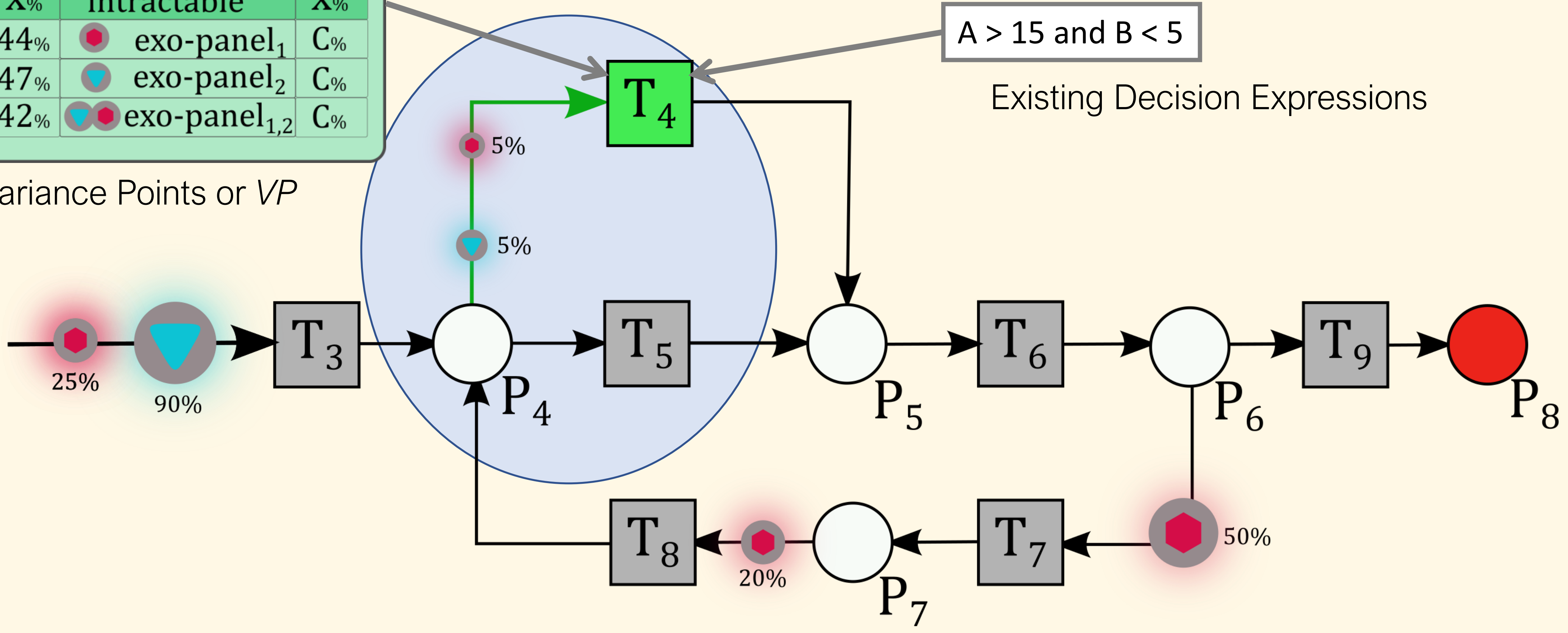
*RQ THREE*
*How can analysts study the influence of exogenous data on decision-making variance in processes?*

# Problem

**$T_4$ - First Rework**

| | P(VP) | Name | C(exp) |
|---|---|---|---|
| $VP_6$ | 50% | Endogenous | C% |
| $VP_7$ | X% | intractable | X% |
| $VP_8$ | 44% | exo-panel$_1$ | C% |
| $VP_9$ | 47% | exo-panel$_2$ | C% |
| $VP_{10}$ | 42% | exo-panel$_{1,2}$ | C% |

Variance Points or *VP*

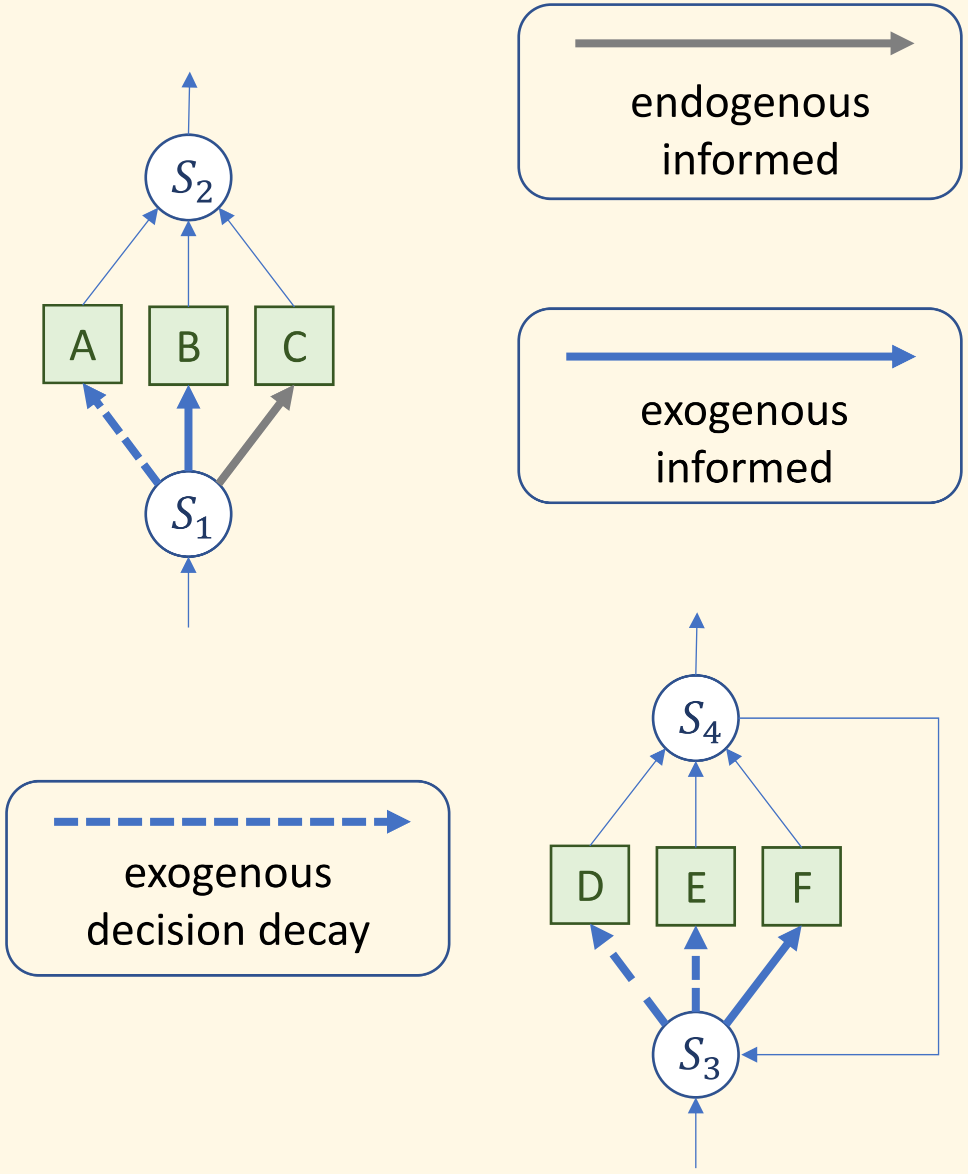



Wind Speed
XX%
exo-panel$_1$

Fire Risk
XX%
exo-panel$_2$

# Planned Outcomes

- A explicit understanding of discovered decision expressions
- Variance points are not static elements
    - Analysis for ‘decision decay’; does a decision expression change if a decision is repeated within an execution or has decision-making changed over time
    - Understanding of  how decision-making occurs in contextual situations based on exogenous data



# Process Mining
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*Research Questions*

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*How can patterns/artefacts in exogenous data be identified and represented for decision-making?*

*How can analysts study the influence of exogenous data on decision-making variance in processes?*

# Project Design

*Our research approach generally follows design science research methodology [24]*

**Rigor**
- Review literature
- Identify existing work
- Benchmark
- Present research gap
- Consider objectives

**Design**
- Design prototype
- Validating prototype addresses objectives
- Comparing with existing techniques

**Relevance**
- Test prototype on unknown processes
- Usefulness and effectiveness for domain uses objectives kept?

Incorporating guidelines for presenting process mining algorithms with guarantees [25]

Define Guarantees

Validate Guarantees

Noise relationship

Study Effectiveness

# Progress to Date

22/02/2021

- Literature review
- Initial design of framework (xPM)
- Initial thesis review
- Stage Two

11/05/2021

- ICPM2021
- Developed xPM
- *Article Submission*
  - *EDBA 2021 Successful*
  - *xPM accepted*
- Started Developing Tool Support

17/09/2021

- Contacted Domain Experts
  - Worked through MIMIC-III data to find exemplar
- Extension of workshop paper
  - Design and development of visualisation technique (EESA)
  - Evaluation of xPM and EESA
- *Workshop Presentation at EDBA, ICPM2021*

20/12/2021

- *Refinement of submission for special issue*
  - *Submitted 11th April*
- Quantitively feedback on approach was received positively
  - Being able to reason about the relevant time series data for decisions

22/03/2022

# Next Steps

**11/05/2022**

- Benchmark and analysis of existing techniques for RQ Two
- Initial design for automatic identification of temporal factors

**01/07/2022**

- Implementation of our design
- Evaluation of our implementation against existing
- Draft article for automatic identification of temporal factors

**01/09/2022**

- Design and Implementation of automated procedure to translate temporal factors to slicing and transforming (xPM)
- *Article for automatic construction of xPM (slicing+transform) configuration*

**01/12/2022**

**01/02/2023**

- Benchmark of probabilistic techniques for decision mining
- Design and Implementation for variance point algorithm

**01/05/2023**

- Evaluation of the algorithm for decision-making variance
- *ICPM2023, BPM2023 submission*
- Development of support tools

**01/09/2023**

- Thesis writing

**22/02/2024**

- Thesis Submission ☺

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**Adam Banham, PhD Candidate**
Principal: Prof Moe Thandar Wynn
Associate: Dr Robert Andrews
External: Prof Sander Leemans

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