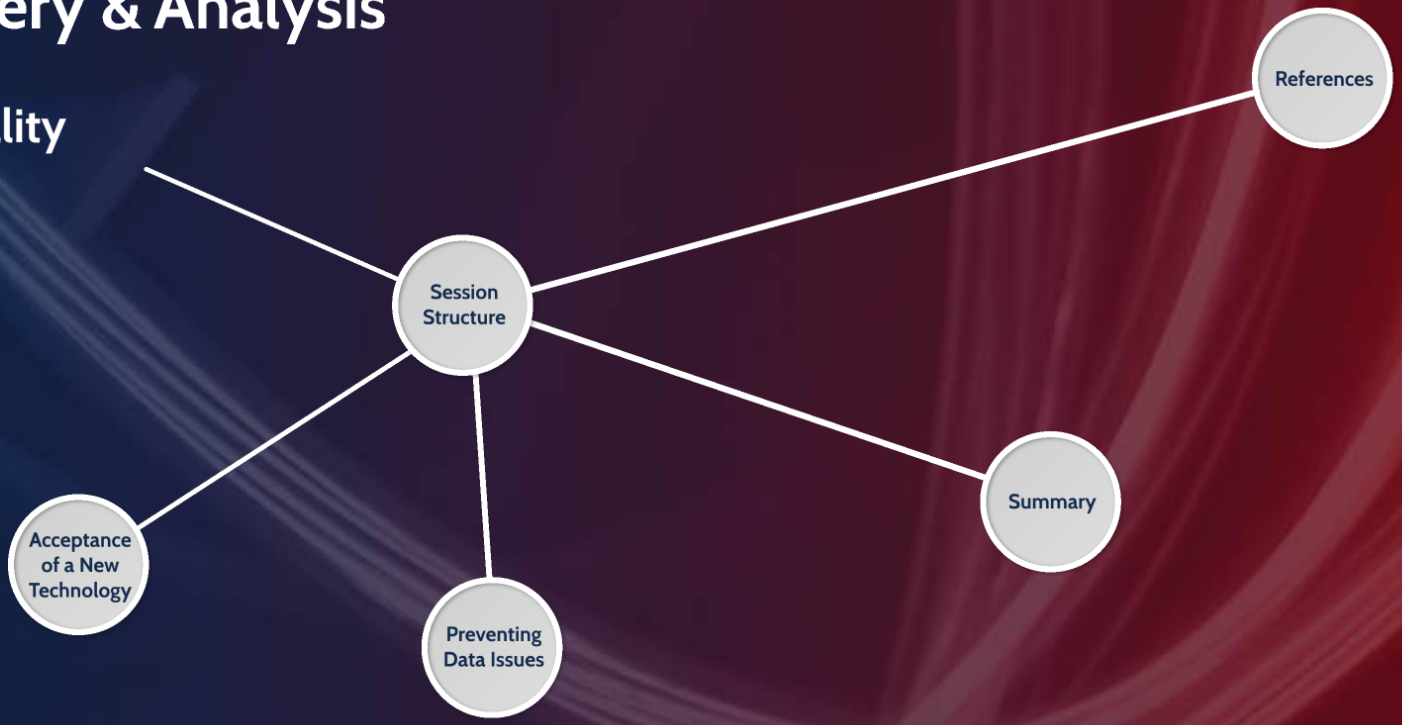
Process Analytics: Turning Data Into Insights

Discovery & Analysis

Data Quality



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Session Structure

Learning Objectives – Data quality

How quality of insights facilitates the acceptance of Process Mining in an organization

How data quality affects the quality of insights

What are the common problems of data quality in the event log

How to prevent the data problems when preparing the event log

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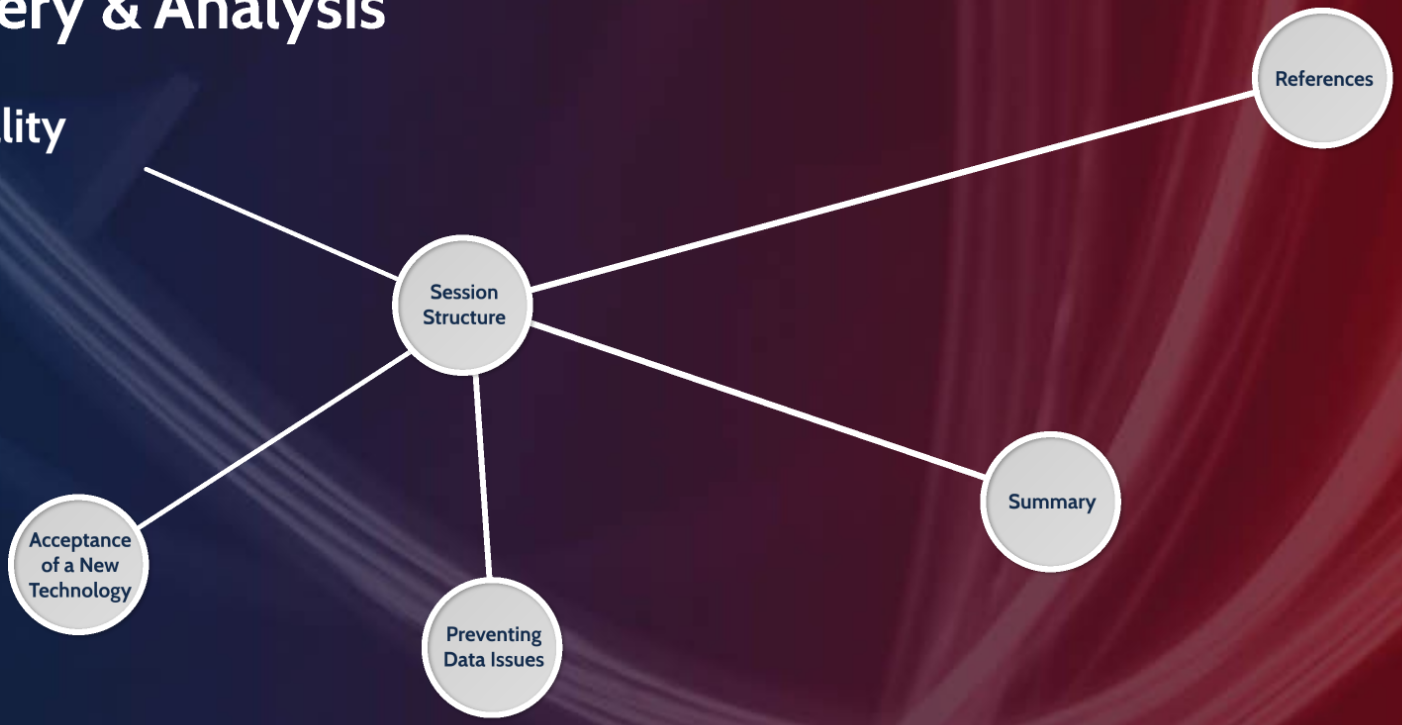

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Acceptance of a New Technology

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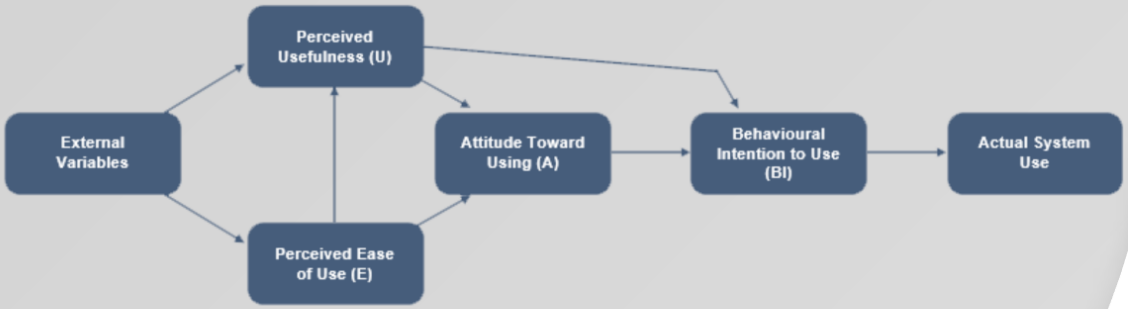
Technology Acceptance Model (TAM) (Davis, 1987)



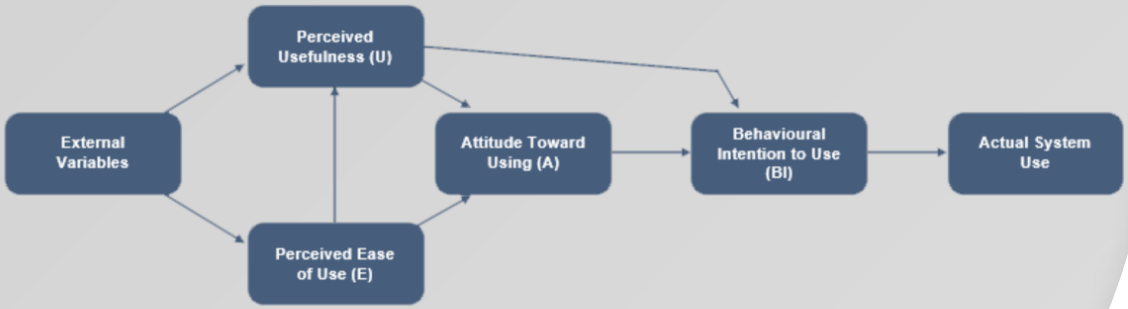
Acceptance of Process Mining

Influencing Factors of Analysis Quality

Acceptance of Process Mining

Acceptance of Process Mining

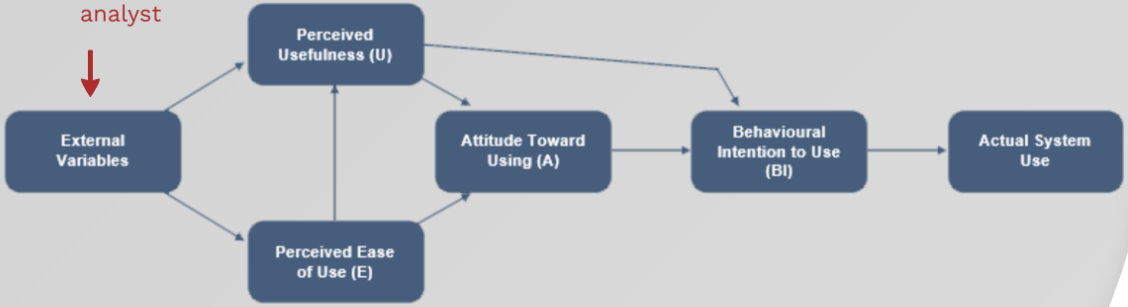
TAM in Process Mining



Acceptance of Process Mining

TAM in Process Mining

e.g. Education of a process analyst



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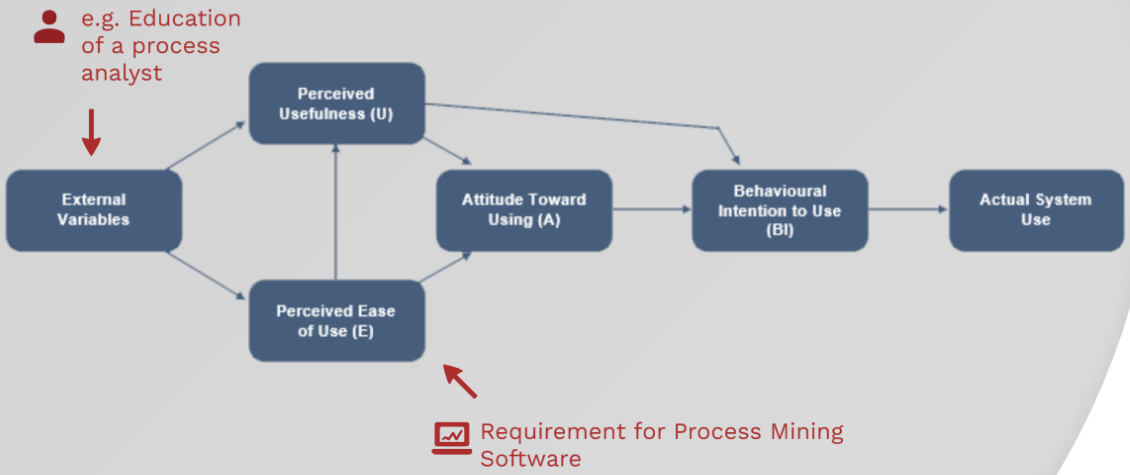

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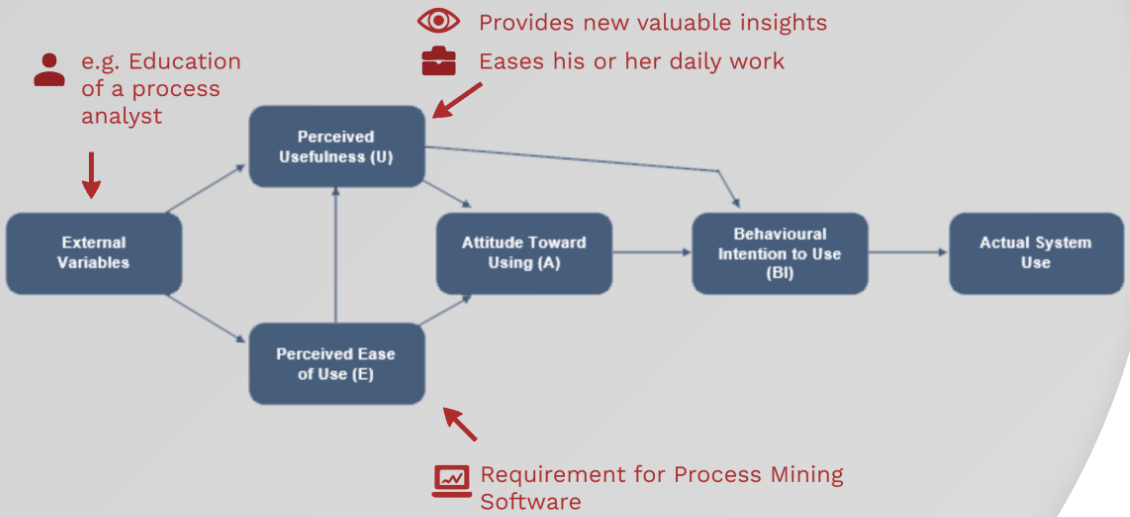

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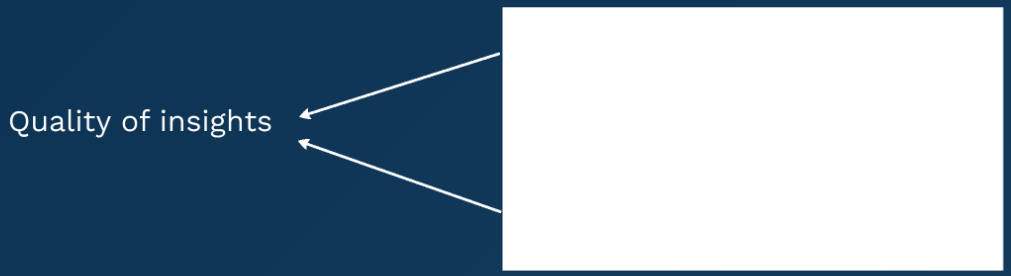
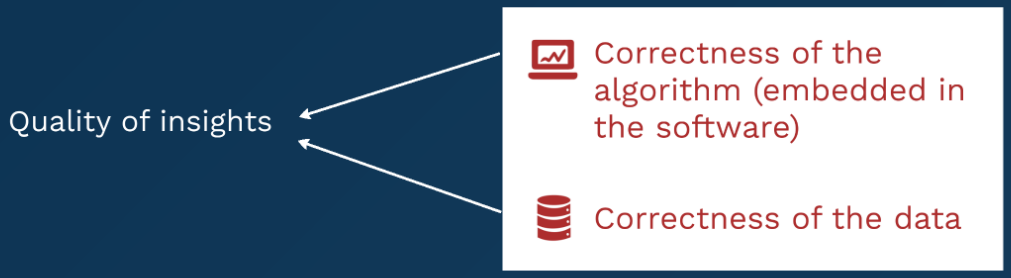


Data Issue 1

Data Issue 2

Influencing Factors of Analysis Quality



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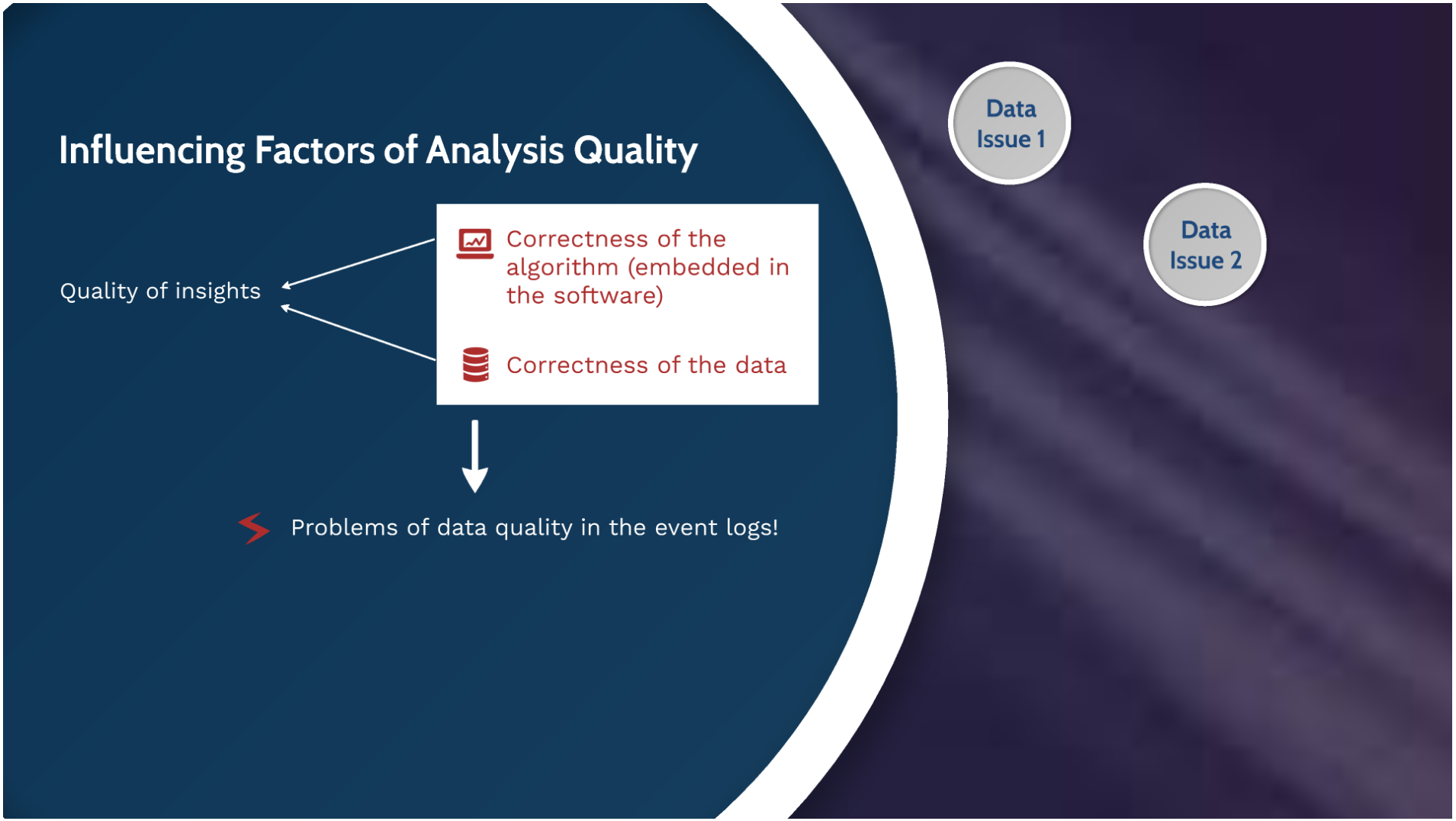


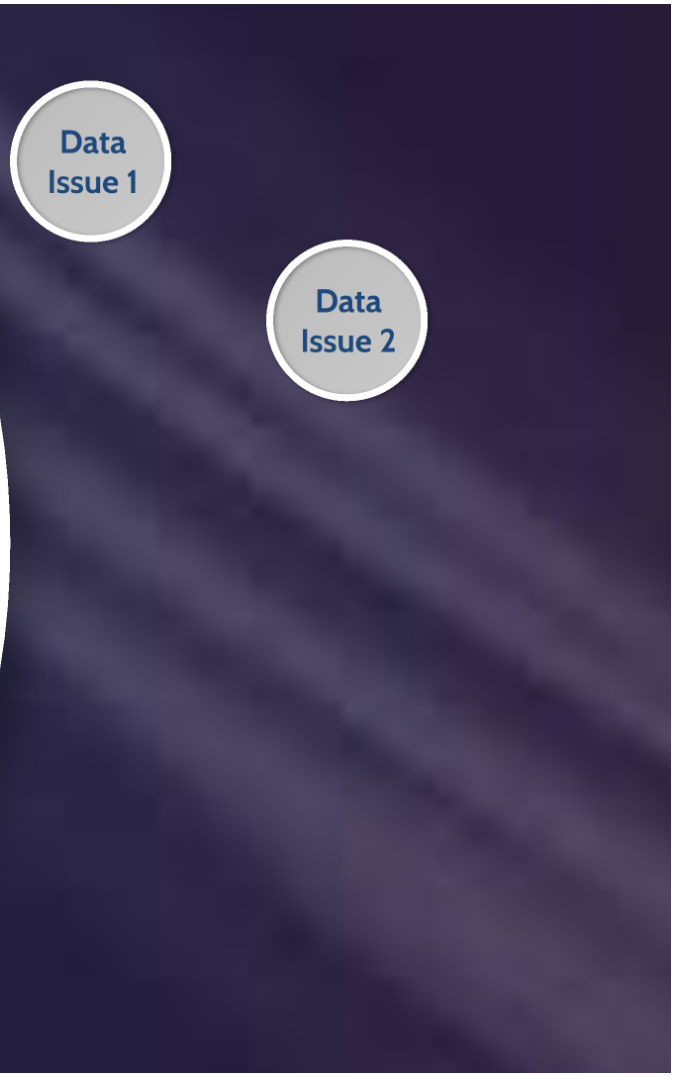
Influencing Factors of Analysis Quality

Quality of insights

- Correctness of the algorithm (embedded in the software)
- Correctness of the data

Problems of data quality in the event logs!

1. **Noise**
2. **Incompleteness**



Data Issue 1 - Noise (Van Der Aalst, 2016)

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Rare and infrequent behavior

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Rare and infrequent behavior

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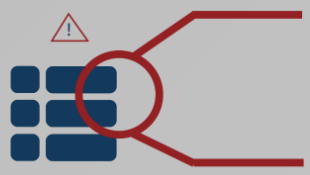

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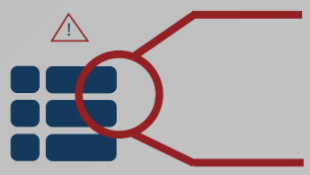

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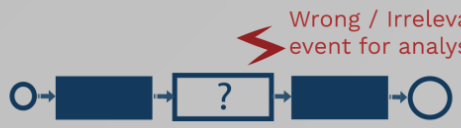

Less meaningful/
comprehensible
results

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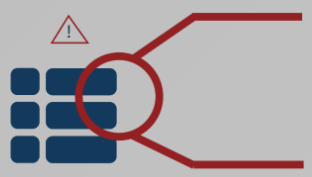

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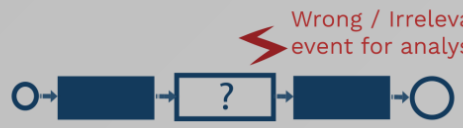

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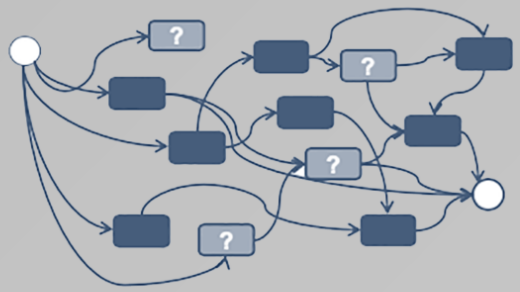

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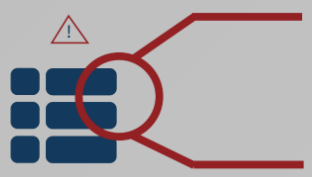

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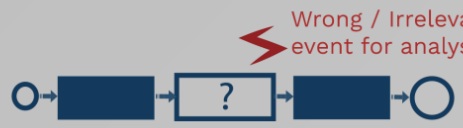

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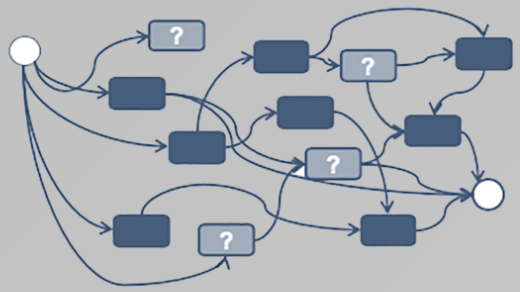

Spaghetti diagram
(Van Der Aalst, 2011)

Data Issue 2 - Incompleteness (Van Der Aalst, 2016)

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Not enough information

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Disable a comprehensive data analysis

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Discovery & Analysis

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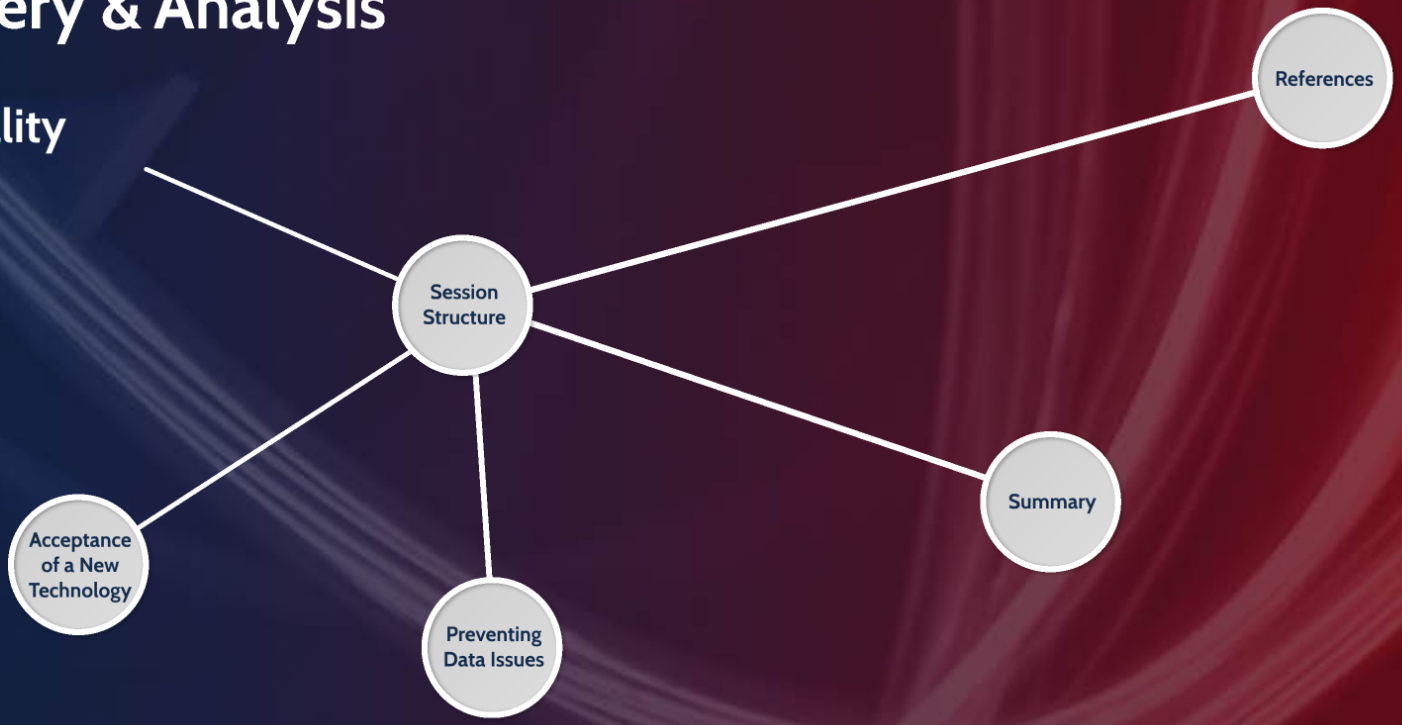

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Preventing Data Issues

Recap:

too much → **1 Noise**

too few → **2 Incompleteness**

Correctness of the algorithm (embedded in the software) ✓

Correctness of the data ✓

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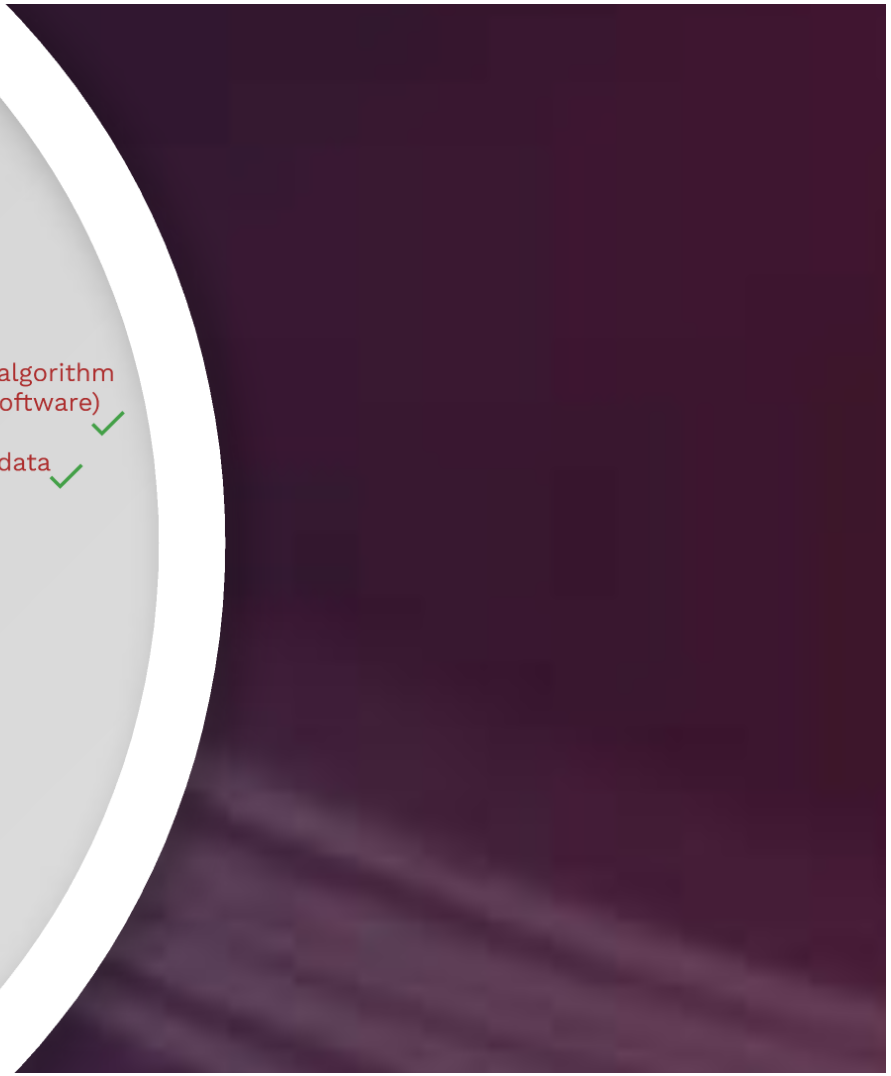
When preparing an event log



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(Van Der Aalst, 2016)

Challenges for Preparing an Event Log - 1

Correlation (Van Der Aalst, 2016)

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Focus: link all process steps for one case

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Correlation (Van Der Aalst, 2016)

Focus: link all process steps for one case

E.g. Sales process: Sales Order

Challenges for Preparing an Event Log - 2

Timestamps (Van Der Aalst, 2016)

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★ **The time of execution for each activity (start and end) is tracked in detail**

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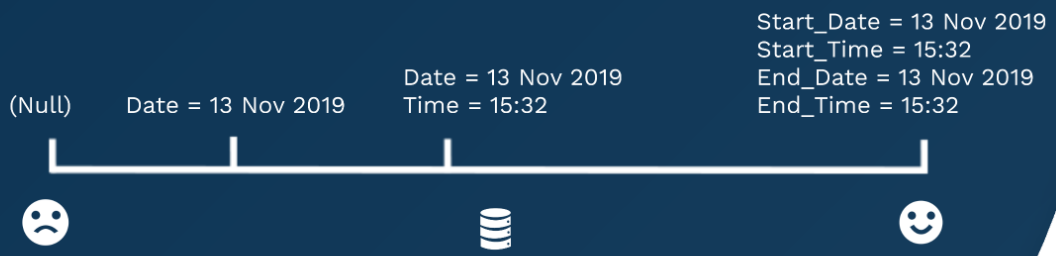

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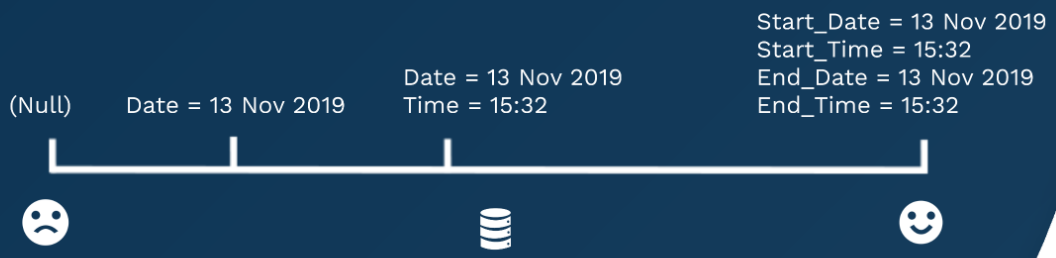

⚠ Process Mining cannot be done without the timing & order of the activities

Challenges for Preparing an Event Log - 3

Snapshots (Van Der Aalst, 2016)

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★ Covering each case from **start** 

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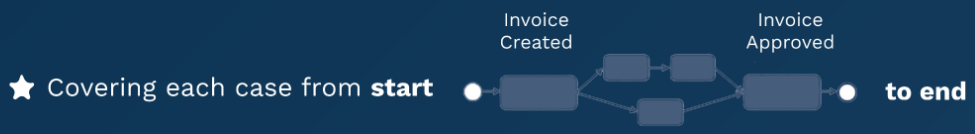

E.g. analysis period: 2019-01-01 – 2019-12-31

Challenges for Preparing an Event Log - 3

Snapshots (Van Der Aalst, 2016)

★ Covering each case from **start** **to end**

E.g. analysis period: 2019-01-01 – 2019-12-31

⚠ Missing a part of each case

Challenges for Preparing an Event Log - 4

Scoping (Van Der Aalst, 2016)

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★ **"start" & "end" of the process**

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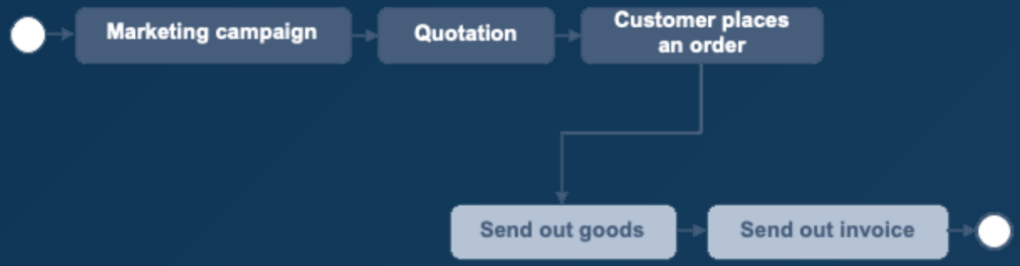

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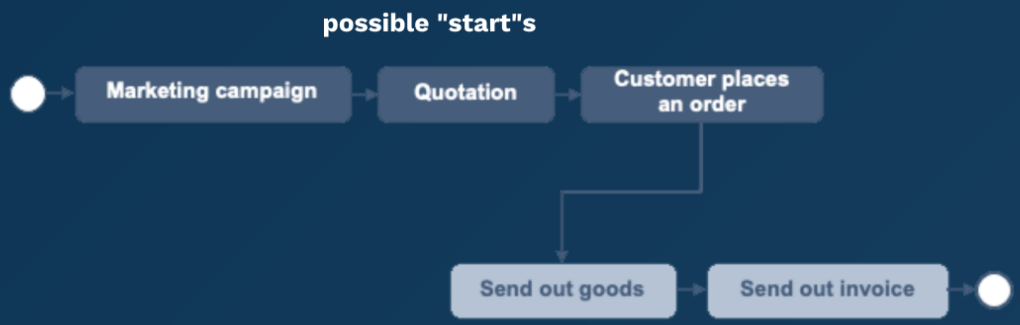

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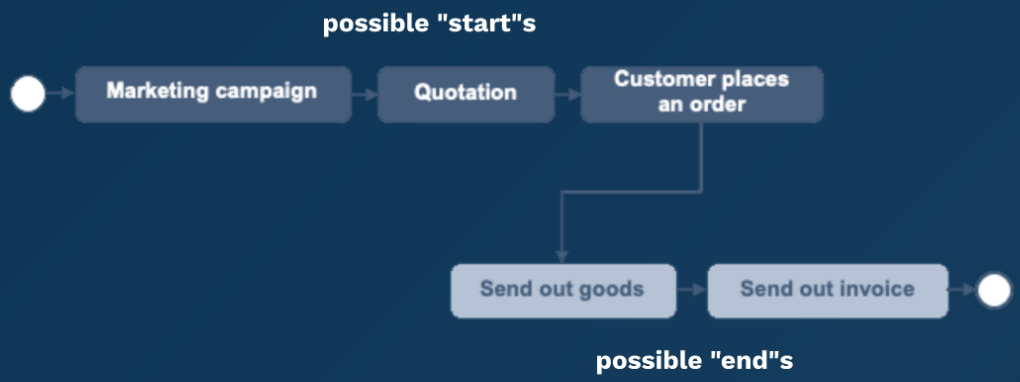

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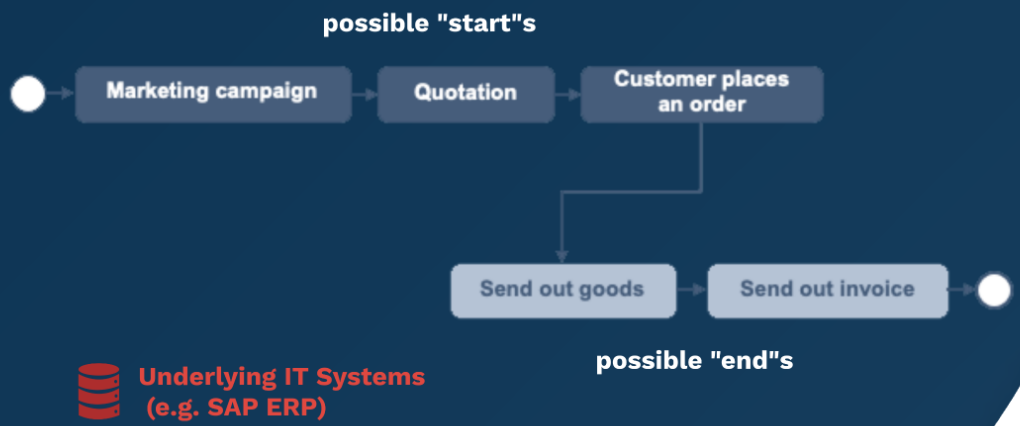

Underlying IT Systems (e.g. SAP ERP)

Challenges for Preparing an Event Log - 5

Granularity (Van Der Aalst, 2016)

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★ **Right level of depth & detail**

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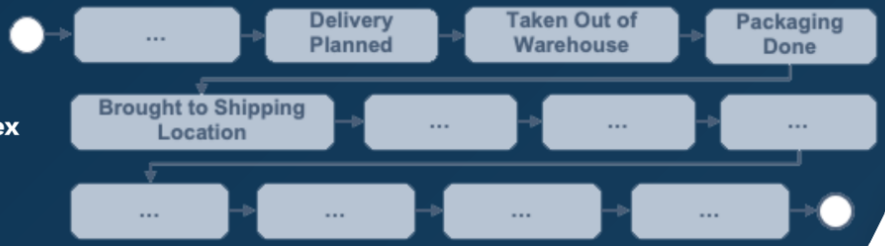
Too complex



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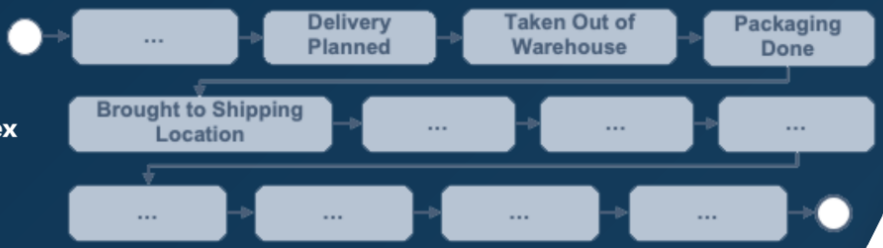

⚠ Balance of complexity and detail that yields insights

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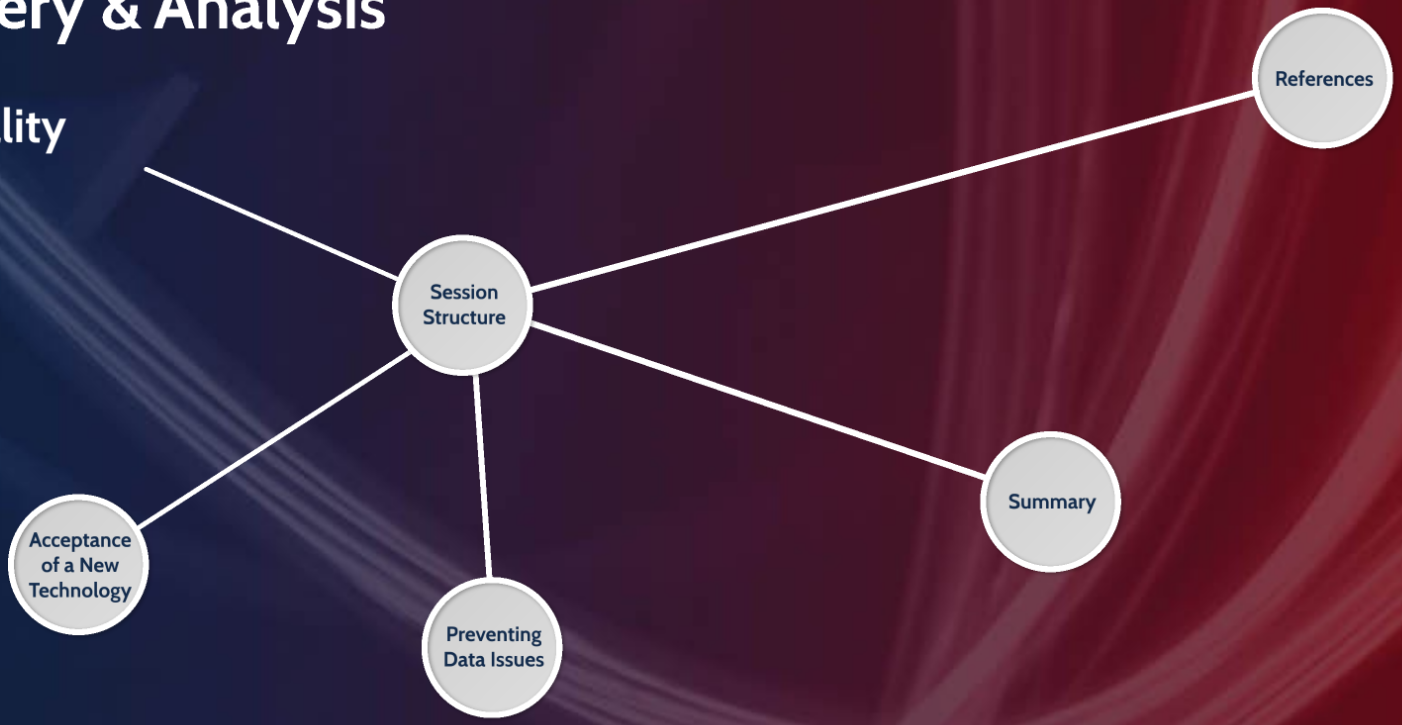

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Summing Up

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2 **common problems in data sets**

Summing Up

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- Noise
- Incompleteness

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5 challenges of ensuring data quality

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★ High-quality event log = Meaningful results

Summing Up

2 common problems in data sets

- Noise
- Incompleteness

5 challenges of ensuring data quality

- ★ High-quality event log = Meaningful results
- ★ Correct & meaningful results = Trust in your solution

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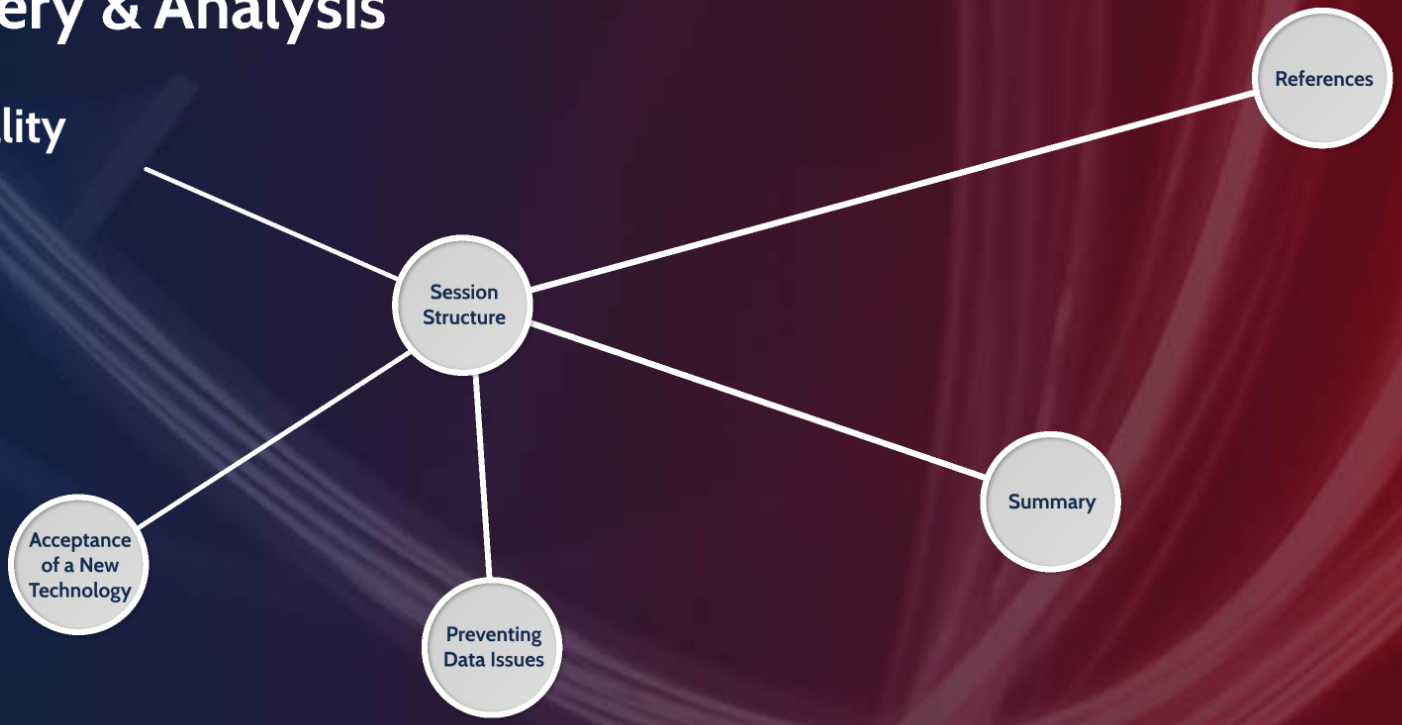

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References

1. Davis, F. (1987). User Acceptance of Information Systems: The Technology Acceptance Model (TAM). 1st ed.

2. Van Der Aalst, W. (2016). Process Mining: Data Science in Action (2nd ed.). Heidelberg: Springer.

3. Van Der Aalst, W. M. (2011, April). Process mining: discovering and improving Spaghetti and Lasagna processes. In 2011 IEEE Symposium on Computational Intelligence and Data Mining (CIDM) (pp. 1-7). IEEE.

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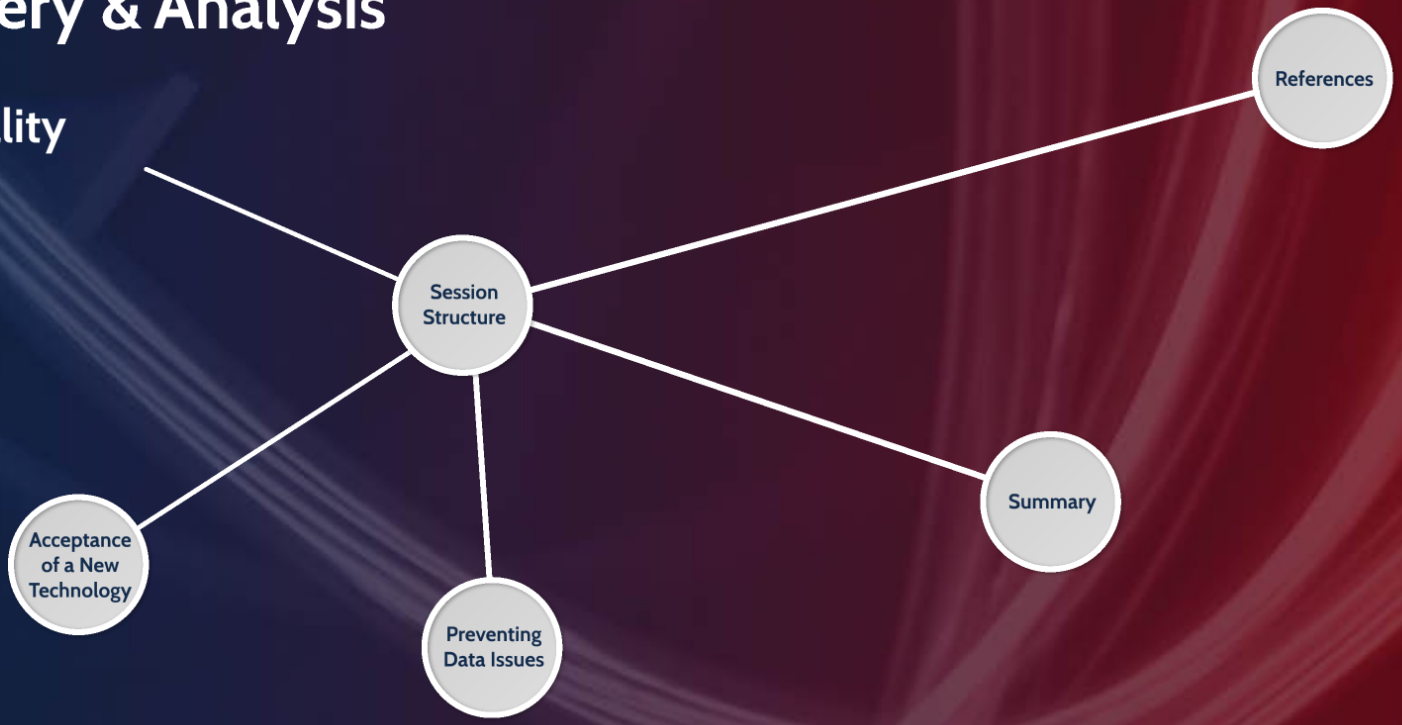

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