



Leveraging Digital Trace Data to Investigate and Support Human-Centered Work Processes

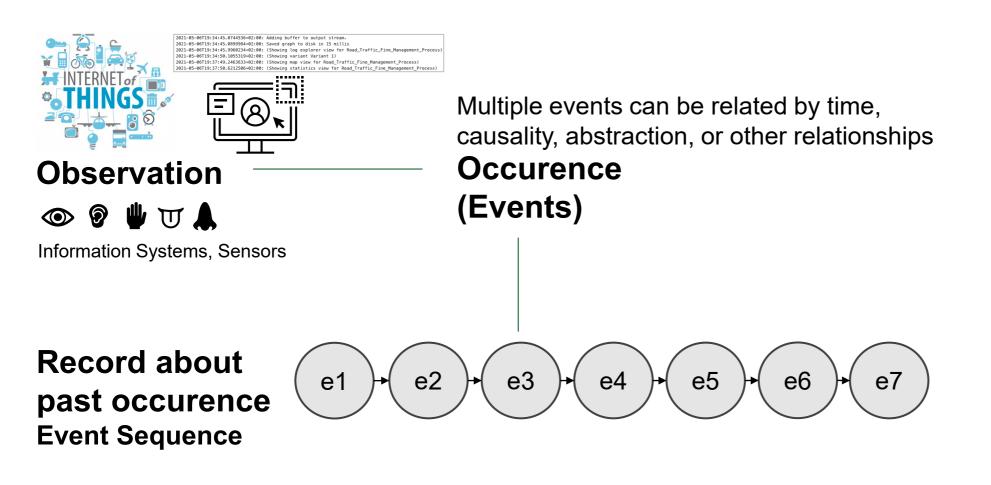
Presented by Barbara Weber

Leveraging Digital Trace Data to Investigate and Support Human-Centered Work Processes, ICEIS/ENASE Keynote on April 25th, 2023, Prague, Czech Republic



Digital Trace Data

Digital technologies create an ever-increasing volumne of digital traces.





Process Mining on the Rise

EDITORS' PICK | Jun 2, 2021, 06:00am EDT | 63.454 views

Celonis Raises \$1 Billion At \$11 Billion Valuation, Making It New York's —And Germany's — Most Valuable Startup

INSIGHTS

SAP to acquire Business Process automation startup Signavio for a reported US\$1.2 billion

Staff Writers / ③ Thu 28 Jan 2021 Insights > SAP to acquire Business Process automation startup Signavio for a reported US\$1.2 billion

> US giant Salesforce partners with software startup Apromore after \$15.3m capital raise

By Nick Nichols

IBM acquires Italy's myInvenio to integrate process mining directly into its suite of automation tools

Ingrid Lunden @ingridlunden / 2:03 PM GMT+2 • April 15, 2021



Appian acquires process mining company Lana Labs

Kyle Wiggers @Kyle_L_Wiggers August 5, 2021 2:05 PM

f 🎔 in

Microsoft acquires process mining vendor Minit to grow its automation offerings

Kyle Wiggers @kyle_I_wiggers / 9:05 PM GMT+2 • March 31, 2022

Comment



6 December 2022



Magic Quadrant for Process Mining Tools

- Gartner published a market guide for process mining in 2018
- Inaugural publication of a Magic Quadrant for Process Mining tools in 2023





The Potential of Process Mining



Creation of «current state» processes

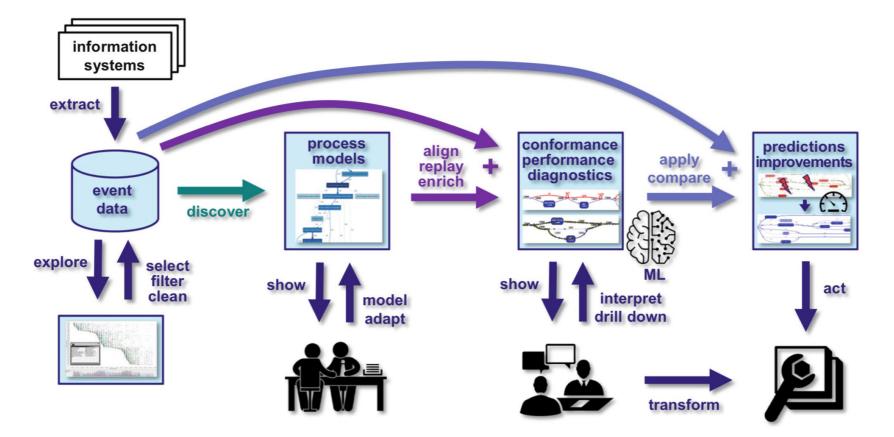
Connecting BPM with Data

"Process mining software can help organizations easily capture information from enterprise transaction systems and provides detailed — and datadriven — information about how key processes are performing."

Source: Davenport and Spanyi, What Process Mining Is, and Why Companies Should Do It



Process Mining: The Big Picture



Source: van der Aalst & Carmona: Process Mining Handbook

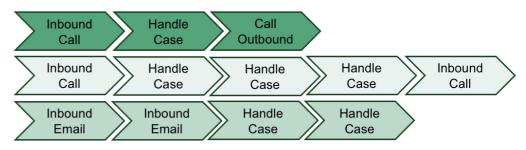


niversität St.Gallen Event Data: The Starting Point for Process Mining

Case	Activity	Start Date	End Date
Case 17	Inbound Call	04.03.2010 07:35	04.03.2010 07:46
Case 17	Handle Case	04.03.2010 07:53	04.03.2010 07:55
Case 17	Handle Case	08.03.2010 11:16	08.03.2010 11:18
Case 1	Inbound Call	09.03.2010 08:05	09.03.2010 08:10
Case 1	Handle Case	11.03.2010 10:30	11.03.2010 10:32
Case 17	Handle Case	11.03.2010 11:15	11.03.2010 11:19
Case 1	Call Outbound	11.03.2010 11:45	11.03.2010 11:52
Case 19	Inbound Email	14.03.2010 14:08	18.03.2010 08:04
Case 17	Inbound Call	14.03.2010 17:53	14.03.2010 17:56
Case 19	Inbound Email	18.03.2010 08:06	18.
Case 19	Handle Case	18.03.2010 08:07	18. Case ID,
Case 19	Handle Case	18.03.2010 08:09	18. per event a

An event log contains traces Each trace is a sequence of events belonging to the same case

Traces of Case 1, 17 and 19



Case ID, activity and at least one timestamp per event are the minimum requirements for an event log



Process science is concerned with understanding and

Process Science Event Data for Studying Continuous Change

Process Science: The Interdisciplinary Study of Continuous Change

Jan vom Brocke University of Liechtenstein jan.vom.brocke@uni.li		Wil M.P. van der Aalst RWTH Aachen wvdaalst@pads.rwth-aachen.de		University of	s Grisold Liechtenstein isold@uni.li
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University	a Roeglinger of Bayreuth linger@fim-rc.de	Michael Rosemann QUT Brisbane m.rosemann@qut.edu.au		University	a Weber of St.Gallen ber@unisg.ch
Abstract			1. Intro	duction	
The only constant in our wor not a field of science that exp change? We propose the e science, a field that studies p of changes, both man-made that unfold over time and	olicitly studies establishment rocesses: cohe and naturally	continuous of process rent series occurring,	phenome involving platformi movemer	na of our time change: Clima zation of econ nts including #	e of process. Many core speak to complex dynamics te change, globalization, the omies, as well as societal 'meToo, #FridaysForFuture, political decisions, have in

common that we can learn a lot more about them if we

"Process science is the interdisciplinary study of continuous change. By process, we mean a coherent series of changes that unfold over time and occur at multiple levels."

Digital trace data offer new opportunities to study **how phenomena evolve** in terms of underlying **sequences of events**.

vom Brocke et al., Process Science: The Interdisciplinary Study of Continuous Change



Process Science Activities

Discovery

Goal. Capture and describe processes.

Example. Methods to create process representations from

digital trace data and to identify patterns in processes.

Explanation

Goal. Understand why, how and when a process unfolds.

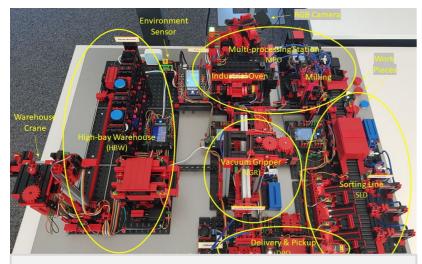
Example. Methods to study the context in which a pattern is situated.



Goal. Intervene and shape the process into desired directions.

Example. Methods to develop and evaluate interventions.



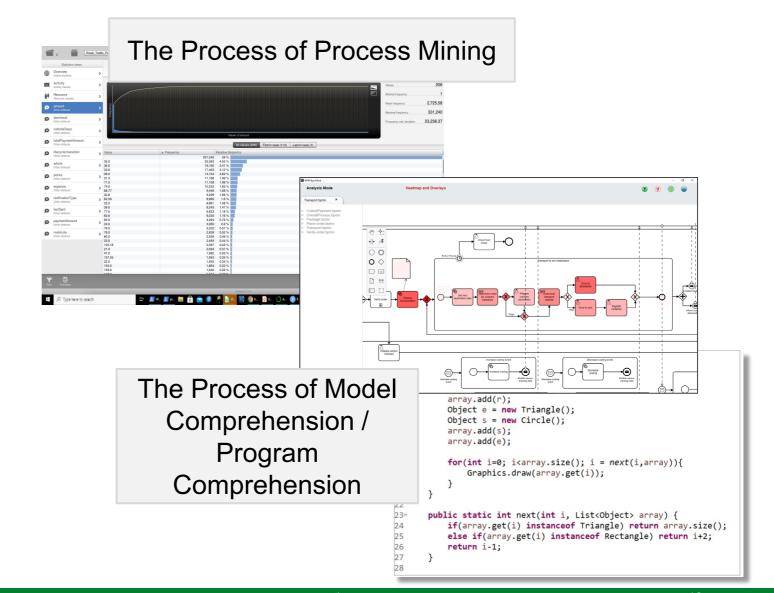


The Process of Storage and Production in a Smart Factory



Phlebotomy: The Process of Drawing Blood

Examples of Different Processes



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Process Science in Action

Selection of Data Sources, Data Collection, and Event Log Generation

Process Discovery and Exploration

Create "Current State" Process Representations, Mine Behavior Pattern, Visualize Event Sequences Conformance Checking

Process Monitoring

Linking Data Sources and Contextualizing Events and Patterns

Interpretable (Bio-)Feedback, (Neuro-)Adaptive Software Systems Data-driven Tool Development



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Example event from factory:

Topic: FTFactory/HBW 1 { "id": "FTFactory/HBW 1", "timestamp": "2020-12-11 13:35:35.50", "i1 light_barrier_interrupted": false, "i2 light barrier interrupted": true, "i3 light barrier interrupted": true, "i4 light barrier interrupted": false, "i5 position switch pressed": true, "i6 position switch pressed": true, "i7 position switch pressed": false, "i8 position switch pressed": true, "m1 speed": 0, "m2 speed": 0, "m3 speed": 0, "m4 speed": 0, "current state": "ready", "current task": "", "current task elapsed_seconds_since_start": 0, "current sub task": "", "failure label": "", "current pos x": 0, "current pos y": 0, "target pos x": 0, "target pos y": 0, "amount of stored workpieces": 0}

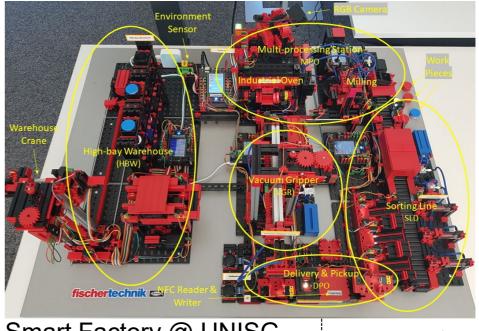
Sensors:

- Switches
- Light barriers
- Color sensors
- Environment
- Camera
- NFC

Actuators:

- Motors
- Compressors
- Valves

Smart Factory equipped with **sensors** and **actuators** emitting **events**



Smart Factory @ UNISG

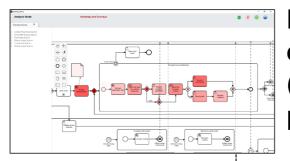
High

Low

Source: R. Seiger, L. Malburg, B. Weber, R. Bergmann, Integrating process management and event processing in smart factories: A systems architecture and use cases.

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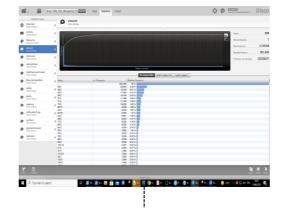


Navigation, scrolling and zooming events during model comprehension (depending on tool); large parts of the process occur in the **reader's mind**

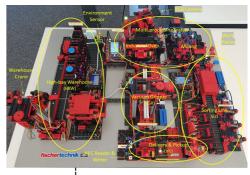
Process is largely manual; no events since most parts performed outside of any IT system

Low

Tool interaction events during analysis (depending on the tool); large parts of the process occur in the **analyst's mind**

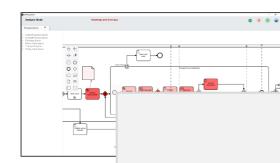


Sensors and actuators emitting events



High





Navigation, scrolling and zooming events during model comprehension (depending on tool): large parts of the

Process is largely n no events since mo performed outside o system

Low

Usage of sensors and additional forms of data collection to increase process observability.

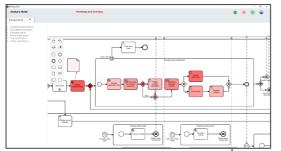
nsors and tuators emitting ents

High

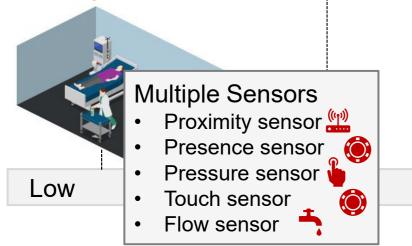


Ø mehoda



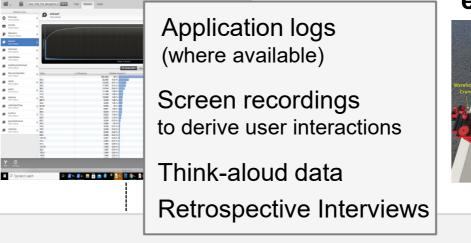


Process is largely manual; no events since most parts performed outside of any IT system



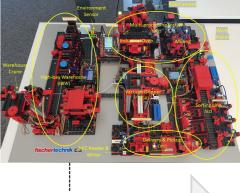
Navigation, scrolling and zooming events during model comprehension (depending on tool); large parts of the process occur in the **reader's mind**

> **Tool interaction events** during analysis (depending on the tool); large parts of the process occur in the **analyst's mind**





Sensors and actuators emitting events



High

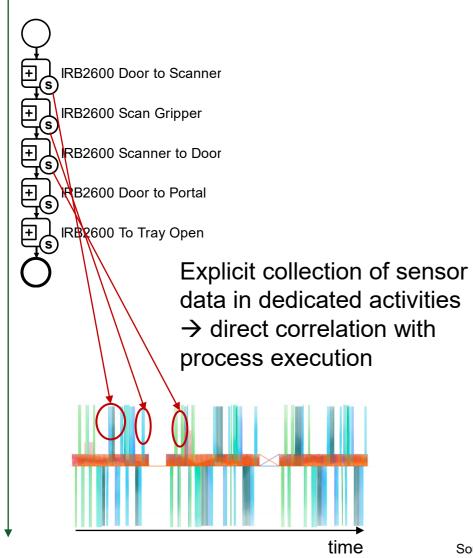


The Importance of Data Collection

- Data collection needs to be carefully planned to enable the linking of the collected data with the different elements of the process
 - -Collecting data in a process context
 - -Synchronized data collection



Top down



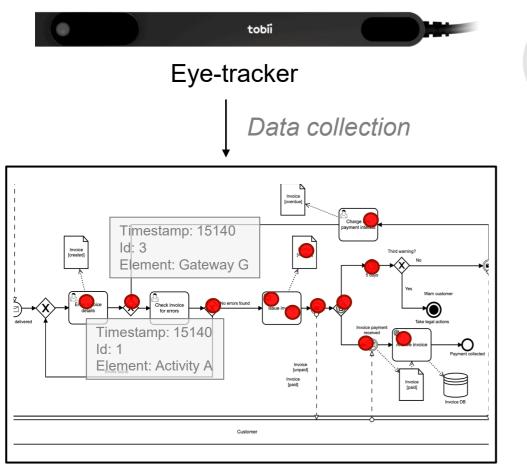
Process-driven Execution and Collection of IoT Data in Context

- IoT data is collected during process execution and gets embedded in the broader process context
- This results in **IoT-enriched event logs** which associate sensor data with the corresponding process execution events

Source: Mangler et al., DataStream XES Extension: Embedding IoT Sensor Data into Extensible Event Stream Logs



Automated Mapping of Attentional Processes to Software Design Artifacts



Automated mapping of gazes to elements of the artifact



- **Gaze events** are automatically mapped during data collection to the elements of the software design artifact (here process model)
- This results in an enriched log of gaze events which associates gaze data with the corresponding elements of the artifact

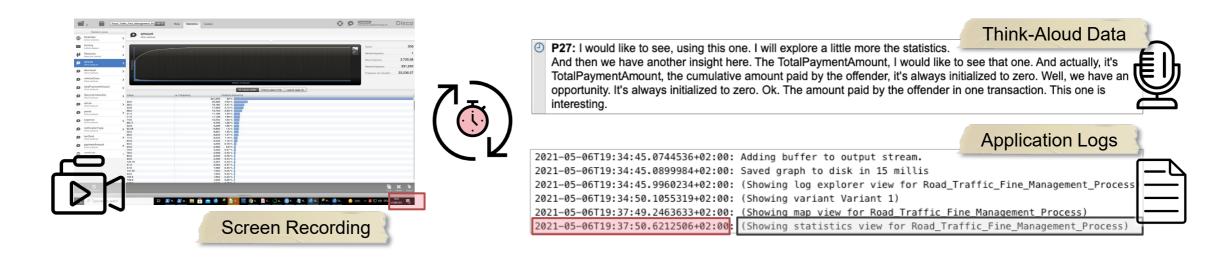
Source: Prototype developed by Amine Abbad Andaloussi



Synchronized Collection of Data

Collecting data in a process context is not always feasible.

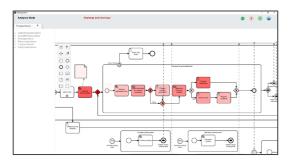
If collected in a synchronized manner, links between different modalities can be established at later stages, e.g., using timestamps.

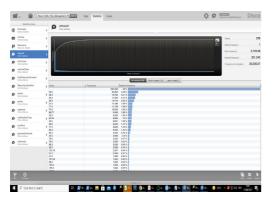




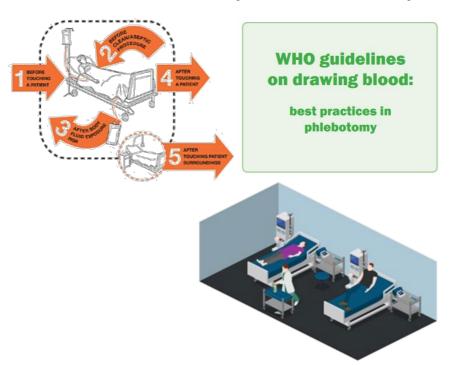
Availability of Process Knowledge

Process and **activities** largely **unknown**; high flexibility and variability

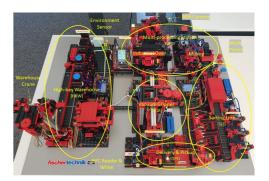




Guidelines including **process steps;** indication for hand hygiene (**business rules**); some flexibility and variability



Process and **activities known**; end-to-end visibility due to processdriven execution and data collection; repetitive and well structured



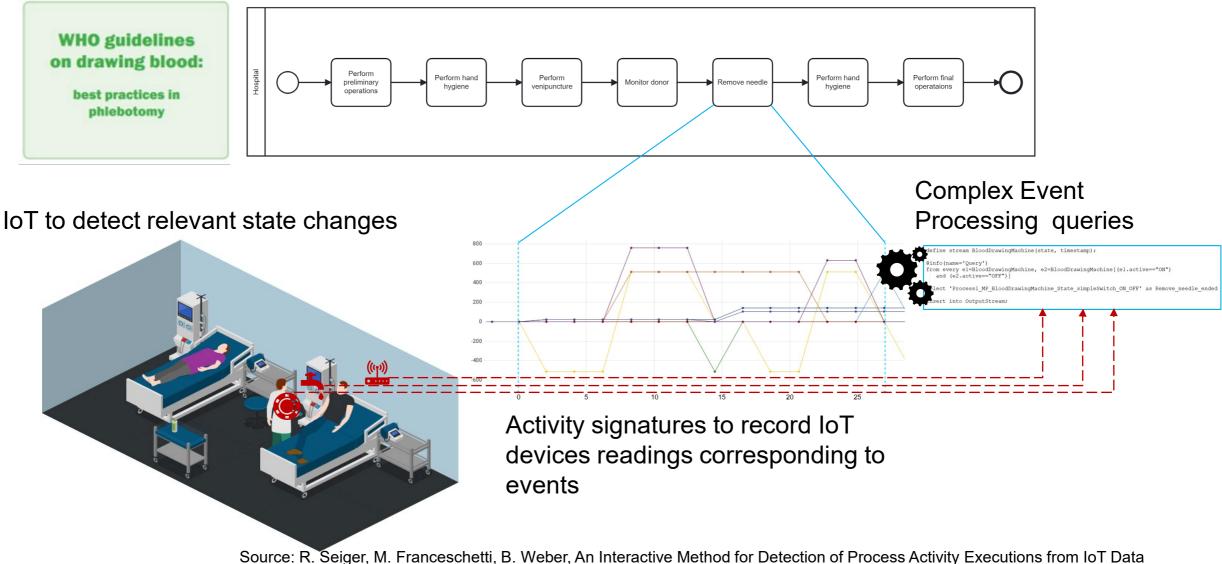
High

Low



Process Activity / Event Detection from Sensors

Known process and activities

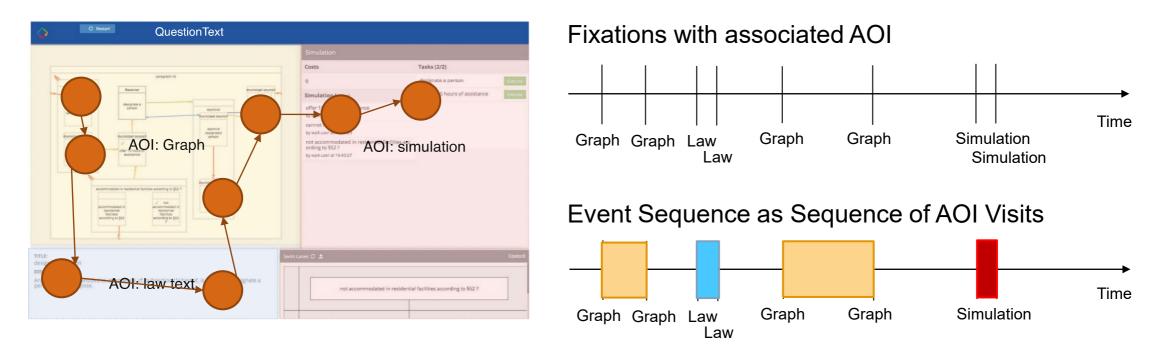


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Areas of Interest as Activity Proxies

- Each comprehension task performed by a participant (i.e., trial) is considered a process instance
- Visits to Areas of Interest (corresponding to elements of the artifact) are used as proxies for activities



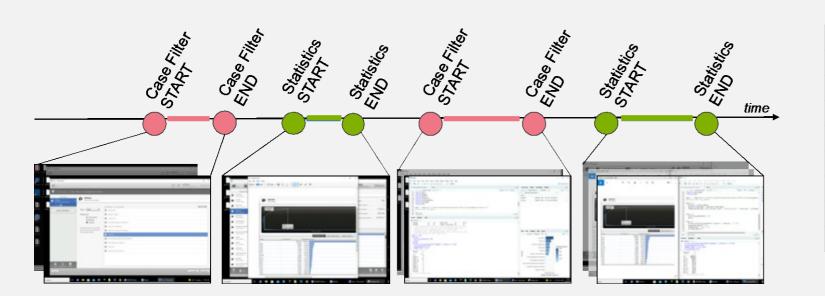
Source: Abbad Andaloussi et al., Exploring how users engage with hybrid process artifacts based on declarative process models: a behavioral analysis based on eye-tracking and think-aloud





Creating User Interaction Logs From Screen Recordings

Since processes and activities are largely unknown, decisions on **what to consider as events** is left to the researcher.



I	Tool Function	Tool	Start	End
P27	PDF Reader	Acrobat Reader	00:04:50,3	00:06:17,4
P27	Case Filter	Disco	00:09:38,3	00:11:09,9
P27	Statistics	Disco	00:11:46,1	00:12:34,3
P27	Case Filter	bupaR	00:14:00,7	00:15:09,9
P27	Statistics	bupaR	00:16:37,1	00:16:59,8
P27	Statistics	Disco	00:16:37,1	00:16:59,8



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Process Discovery and Exploration

Create "Current State" Process Representations, Mine Behavior Pattern, Visualize Event Sequences Conformance Checking

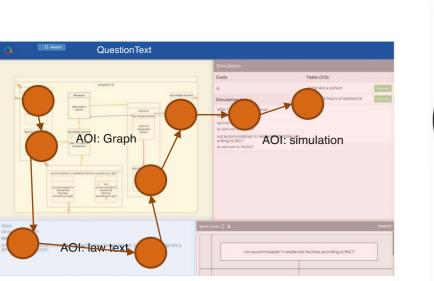
Process Monitoring

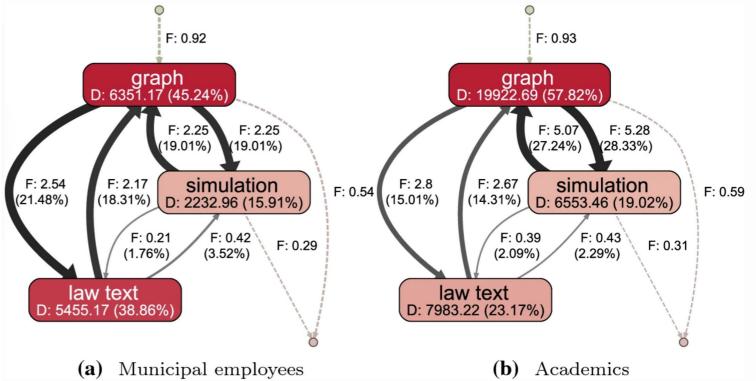
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Interpretable (Bio-)Feedback, (Neuro-)Adaptive Software Systems Data-driven Tool Development



Mining User Behavior Patterns Example: Hybrid Process Artifacts



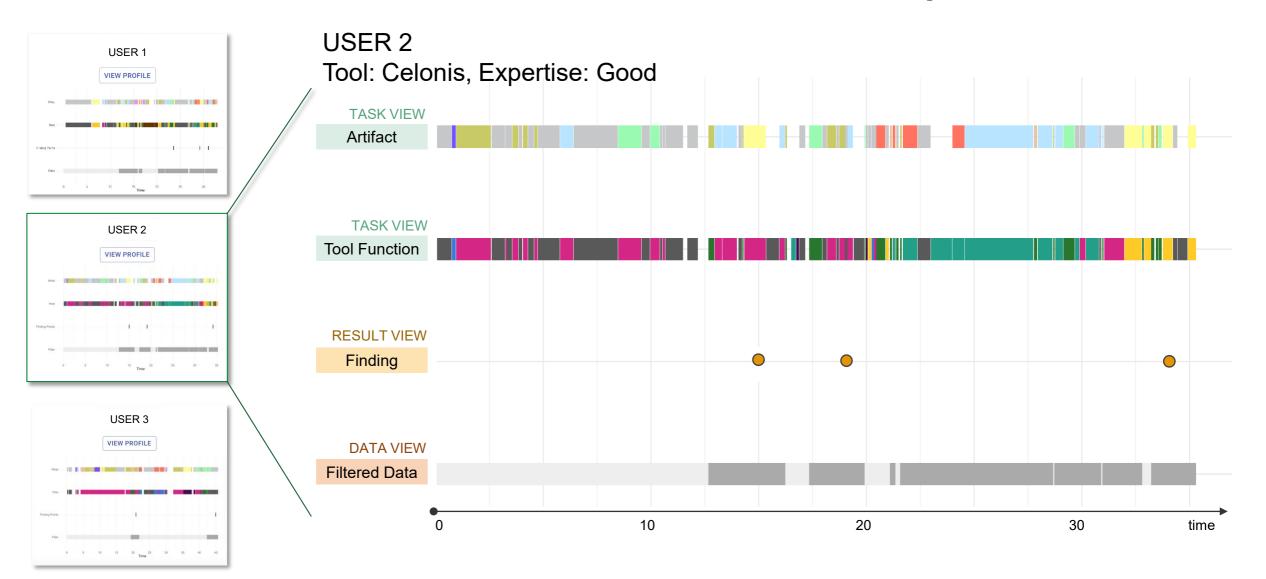


Attention maps in form of Directly-Follow-Graphs comparing the attentional processes for municipal employees and academics. *D* is the mean fixation duration, and *F* is the mean transition frequency between two AOIs.

Source: Abbad Andaloussi et al., Exploring how users engage with hybrid process artifacts based on declarative process models: a behavioral analysis based on eye-tracking and think-aloud



Visualizing Event Sequences Creation of Multi-Perspective Profiles





Visualizing Event Sequences Focus on Subsequences of Interest





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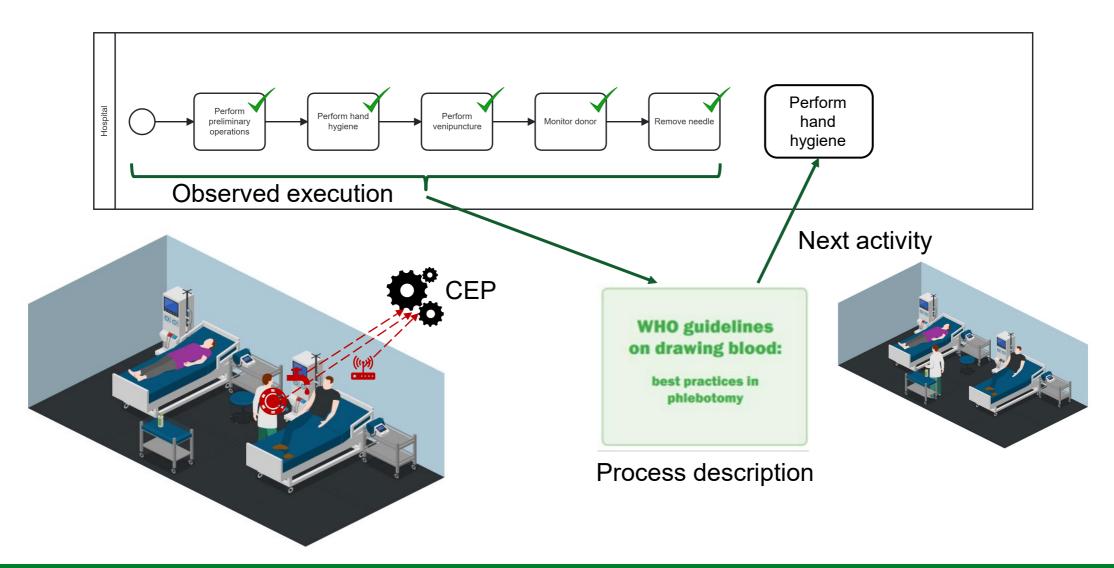
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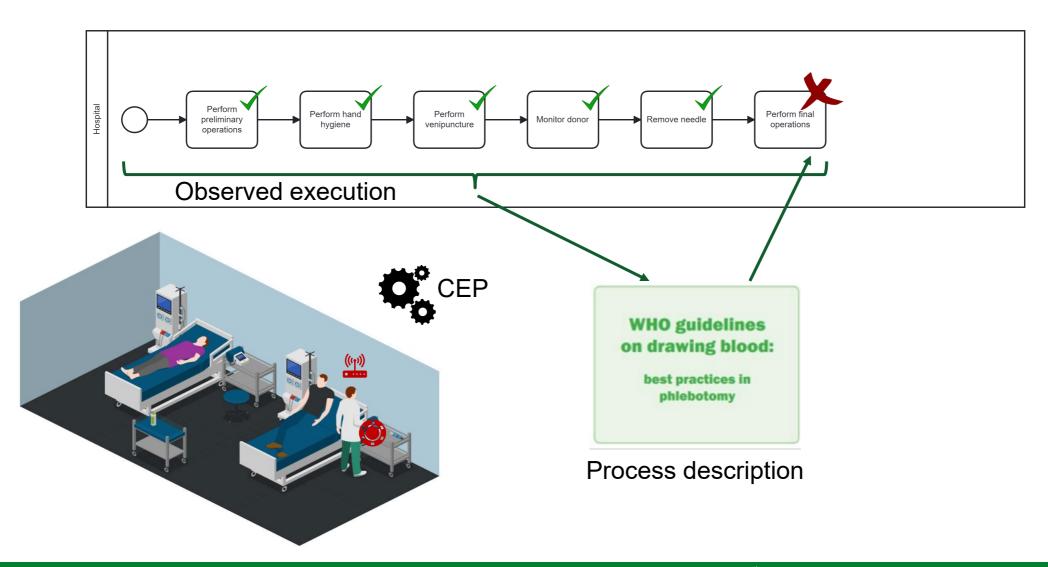


Monitoring for Hand Hygiene Indications





Process Conformance Checking





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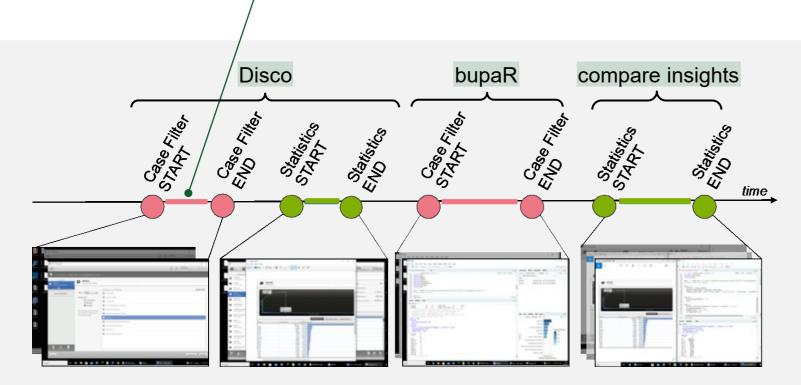
Interpretable (Bio-)Feedback, (Neuro-)Adaptive Software Systems Data-driven Tool Development



Providing Context to User Interaction Logs

Think-Aloud Data

[00:09:38,3 – 00:11:09,9] "I'm trying to filter the Payment activity to see all the cases that we don't have a payment. I've tried using the filter forbidden..."

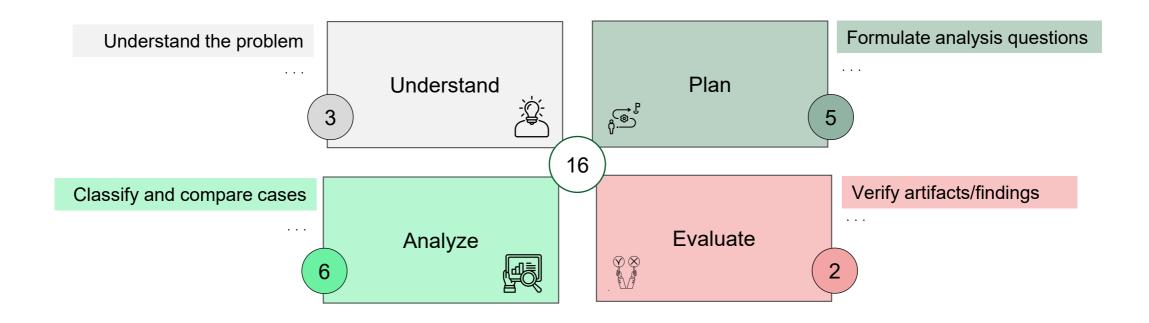


ID	Tool Function	Tool	Start	End
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P27	Statistics	bupaR	00:16:37,1	00:16:59,8
P27	Statistics	Disco	00:16:37,1	00:16:59,8



Providing Context to User Interaction Logs Usage of Common Strategies

Process mining strategies derived from the analysis of interview data.

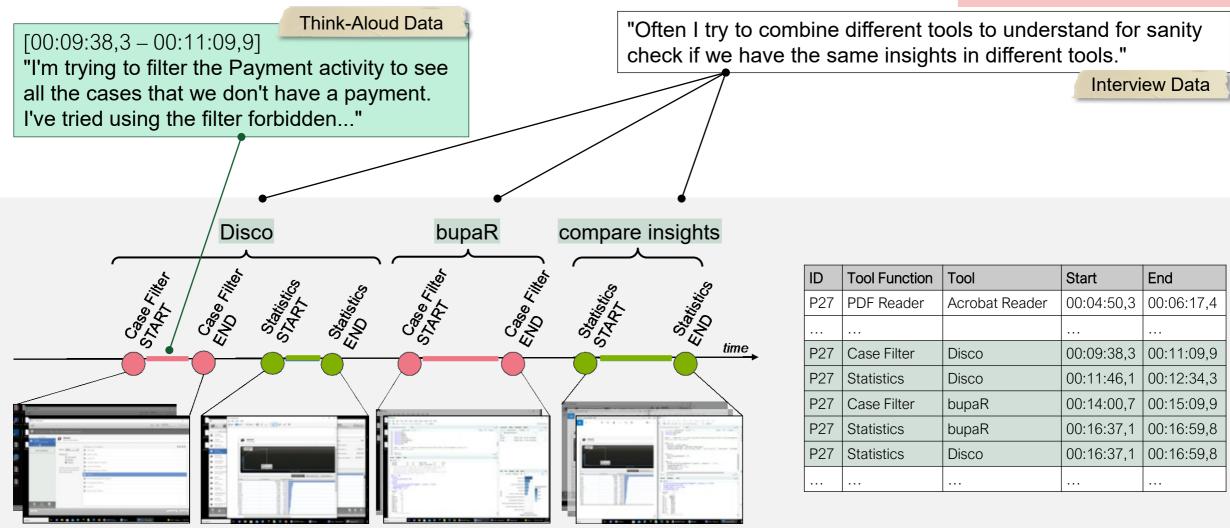


Source: F. Zerbato, P. Soffer, B. Weber, Process Mining Practices: Evidence from Interviews.



Providing Context to User Interaction Logs

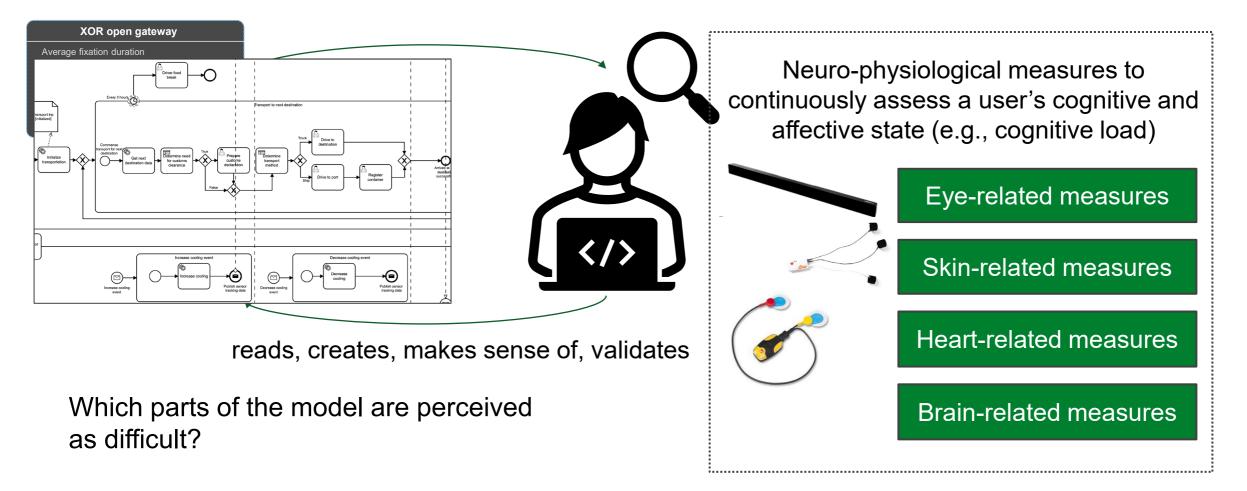
Strategy: Verify artifacts and findings





Associating a User's Cognitive and Affective State With a Software Design Artifact

changes user's cognitive and affective state



Source: Amine Abbad-Andaloussi, Thierry Sorg, Barbara Weber: Estimating Developers' Cognitive Load at a Fine-grained Level Using Eye-tracking Measures



Process Science in Action

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Process Discovery and Exploration

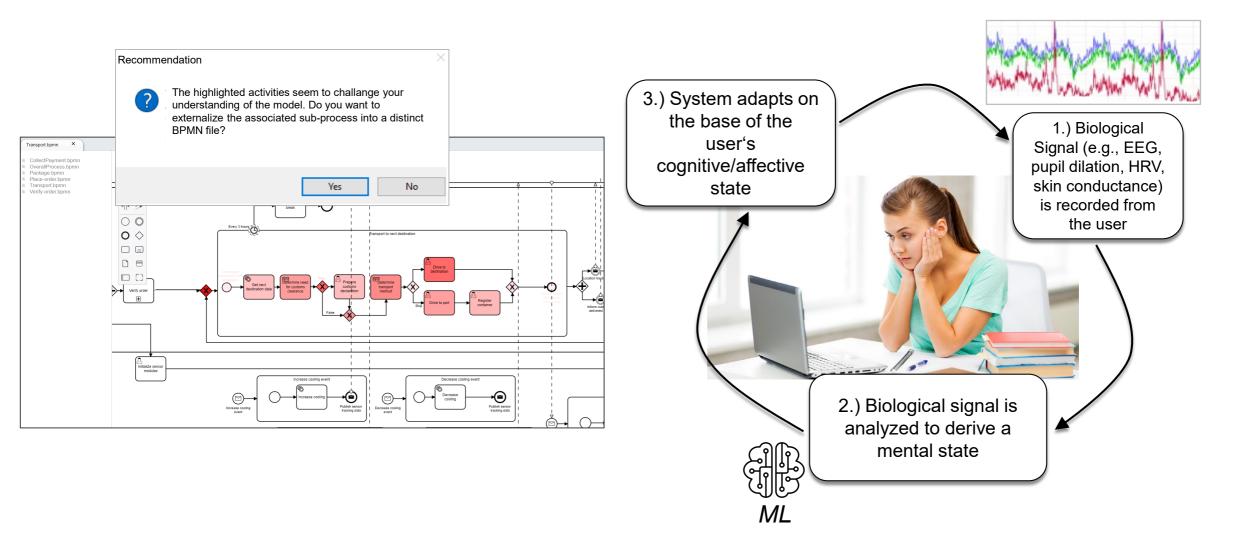
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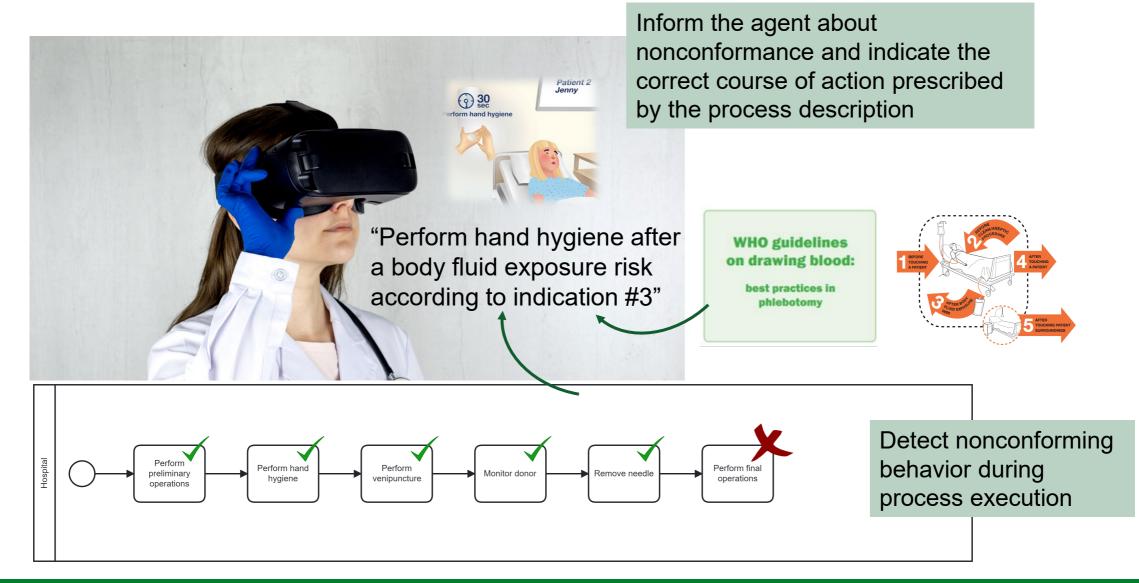
Interpretable (Bio-)Feedback, (Neuro-)Adaptive Software Systems Data-driven Tool Development

Universität St.Gallen Biofeedback and Neuro-adaptive Software Systems





Interpretable Feedback





Data-driven Tool Development

Example of a recorded process mining analysis

	U Id Operation		I/O Timestamp		Timestamp	User Annotations	${\bf G} {\rm oals} \ {\rm and} \ {\bf H} {\rm ypotheses}$	
Г	R	o_1	variantFilter(cases, keep, 75%)	L_0	L_1	$07/10/22 \ 10:01:18$	filtered too much	
	R	\mathbf{v}_1	nCases()	L_1	#cases	$07/10/22 \ 10:01:50$		
2	R		variantFilter(cases, keep, 85%)	L_0	L_2	$07/10/22 \ 10:02:03$	filtered too much	G1: Reduce
3	R		nCases()	L_2	#cases	07/10/22 10:02:32		complexity
	R	03	variantFilter(cases, keep, 90%)	L_0	L_3	$07/10/22 \ 10:03:11$	good trade-off	

Need to (1) maintain provenance information about the analysis, (2) trace analysis goals and insights, (3) increase data awarenesss

R	07	activity riter (cases, keep, "P")	L_6				G3: Vandate
R	O_4	activityFilter(cases, keep, "CC")	L_{12}	L ₁₃	$07/10/22 \ 10:33:44$	filter is correct	combined filter
R	0 ₁₁	activityFilter(cases, remove, CC)	L_{12}	L_{14}	07/10/22 10:36:51		H4: Some partially paid cases do not include CC
R Show results to business stakeholders and auditors G4: Storytelling						G4: Storytelling	
т	O5	activityFilter(cases, remove, "P")	L_3	L ₁₅	$14/10/22 \ 08:33:17$	order of filters	G5: Internal auditing
5	o_4	activityFilter(cases, keep, "CC")	L_{15}	L ₁₆	$14/10/22 \ 08:33:46$	checked	Go. Internal auditing
	R R R	R 04 R 011 R Sh	R o ₁₁ activityFilter(cases, remove, CC) R Show results to business stakeholders and	$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	$ \begin{array}{c c c c c c c c c c c c c c c c c c c $	$ \begin{array}{c c c c c c c c c c c c c c c c c c c $

Supporting Provenance and Data Awareness in Exploratory Process Mining

 $\begin{array}{l} {\rm Francesca\ Zerbato}^{[0000-0001-7797-4602]1},\ {\rm Andrea\ Burattin}^{[0000-0002-0837-0183]2}, \\ {\rm Hagen\ V\"olzer}^{[0000-0003-3547-3847]1},\ {\rm Paul\ Nelson\ Becker^2},\ {\rm Elia\ Boscaini^2},\ {\rm and} \\ {\rm Barbara\ Weber}^{[0000-0002-6004-4860]1} \end{array}$

¹ University of St. Gallen, St. Gallen, Switzerland {francesca.zerbato|hagen.voelzer|barbara.weber}@unisg.ch ² Technical University of Denmark, Kgs. Lyngby, Denmark {s194702|s194720}@student.dtu.dk, andbur@dtu.dk

Abstract. Like other analytic fields, process mining is complex and knowledge-intensive and, thus, requires the substantial involvement of human analysts. The analysis process unfolds into many steps, producing multiple results and artifacts that analysts need to validate, reproduce and potentially reuse. We propose a system supporting the validation, reproducibility, and reuse of analysis results via analytic provenance and data awareness. This aims at increasing the transparency and rigor of exploratory process mining analysis as a basis for its stepwise maturation. We outline the purpose of the system, describe the problems it addresses, derive requirements and propose a design satisfying these requirements. We then demonstrate the feasibility of the central aspects of the design.

Keywords: Process Mining \cdot Exploratory Analysis \cdot System Requirements and Design \cdot Analytic Provenance \cdot Data Awareness \cdot User Support

1 Introduction

Process mining comprises methods to analyze event data generated in information systems during the execution of business processes. Process mining is quickly growing in adoption, and so is its business impact [9].

Like other data science disciplines, process mining requires the substantial involvement of humans, e.g., process analysts, to obtain insights from raw event data [7]. Analysts often freely explore the data with the available tools to gain a basic understanding of what it represents, investigate different scenarios, and create hypotheses. Hypotheses can then be tested using best practices, but more exploration is required if the test fails or the results are inconclusive [19]. Each insight that emerges during the analysis informs which subsequent analysis steps are chosen. On the one hand, the choices made during the analysis yield many possible reasonable results that need to be assessed. On the other hand, such choices might give rise to potential inconsistencies in the analysis process [14].

Due to its knowledge-intensive character and emergent course of action, an exploratory analysis includes many manual and error-prone steps that are often

Source: Francesca Zerbato, Andrea Burattin, Hagen Völzer, Paul Nelson Becker, Elia Boscaini, Barbara Weber: Supporting Provenance and Data Awareness in Exploratory Process Mining.

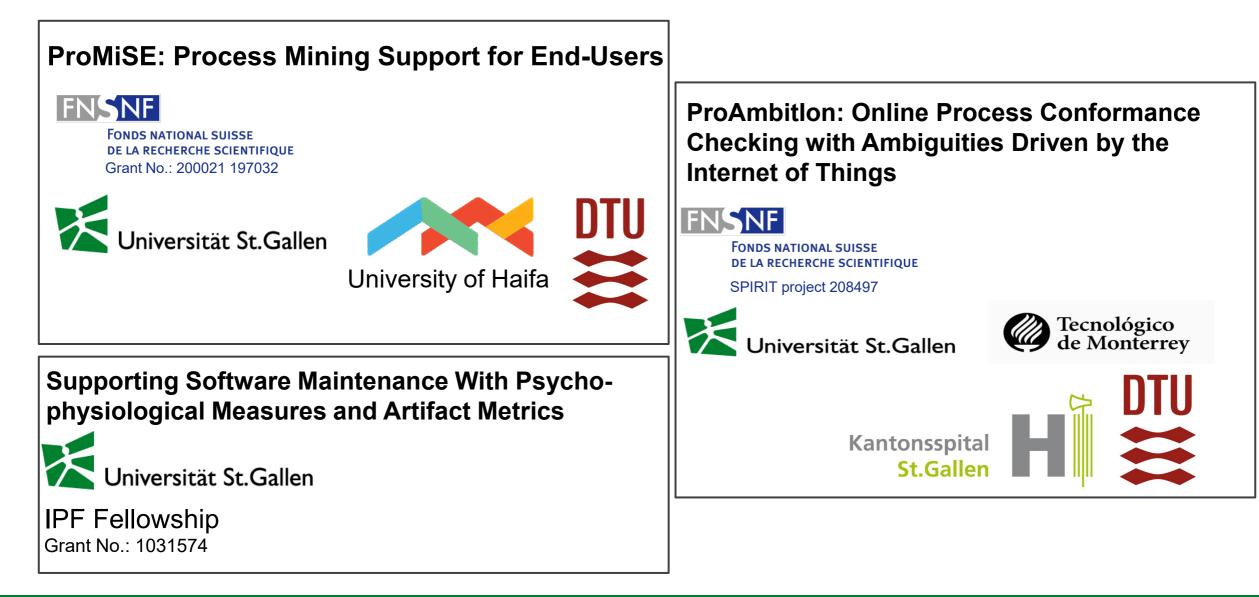
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- Consider leveraging digital trace data beyond traditional business processes
- Carefully planning data collection pays off!
- Going beyond traditional business processes offers great opportunities but brings challenges in terms of process observability, event correlation, and event abstraction









<u>Dr. Amine Abbad</u> <u>Andaloussi</u> IPF Postdoctoral Fellow



Prof. Dr. Ronny Seiger Assistant Professor

Dr. Marco

Franceschetti

Senior Researcher



Thierry Sorg PhD student

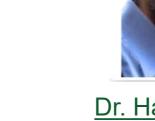


Thank You to My Team

Dr. Francesca Zerbato Senior Researcher







Dr. Hagen Völzer Scientific Project Manager



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