





About the researcher Jan Martin Spreitzenbarth First doctoral employee in the Porsche procurement division

Key facts

- Since 2018 External doctoral student in the Data and Web Science Group at University of Mannheim Supervised by Prof. Dr. Heiner Struckenschmidt with support of Prof. Dr. Christoph Bode
- Research interest in the application of artificial intelligence and machine learning in procurement First paper predicting TCO for supplier selection (ERS 2020 / AACE 2021) Second paper review of AI and ML in procurement (IPSERA 2021) vs sales (ERS and HICL 2021) Third paper simulation workflow (ISDC 2021) with bundling module (EurOMA 2021)
- Since 2016 Buyer at Porsche for infotainment, embedded software, currently requirement management Led by Thomas Pichler and Stephanie Bach, sponsored by Joachim Scharnagl



Interests

Last stations in the CV before joining Porsche

2014 - 2015 Post-graduate scholarship with German Academic Exchange Service DAAD in China Language study in Beijing and IT consultant for an Industry 4.0 project (Smart Factory)

2012 - 2014 Master degree at Karlsruhe Institute of Technology with IBM in Germany MSc in industrial engineering and project buyer of smart meters in Mainz (Smart Home / Smart Energy)

2011 - 2012 Gap year at Robert Bosch in Germany Logistics planner for solenoid valves and metering units at plastics engineering plant in Waiblingen

2009 - 2011 Bachelor degree at Simpson College in the USA Intern at a local automotive supplier in Iowa as well as for an United States Senator in Washington, D.C.

- Team sports e.g. soccer, basketball, and volleyball
- · Travel, languages, and cultures especially Asia
- Nature, hiking, climbing, wine, and horticulture



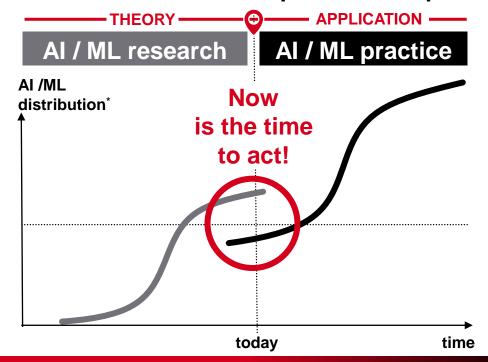
I am looking forward to an interesting discussion with you today!

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Artificial intelligence, now is the time to act!

Al and ML methods offer potential for practical implementation





Data availability

Massive growth of data available

Free software

Open source simplifies implementation

Faster hardware

Technical development enable new applications

Availability of services

Digital providers offer partial AI solutions already

Reality

Long-term research



Science Fiction

"Weak AI"

Assistance or acquisition of specific tasks

with individual solutions

"General AI"

Knowledge transfer from single solutions to larger topics

"Super AI"

Machines are able to **meet** people spiritually

Application of Al and ML are coming out from research into practice.

Source: Al@Porsche project team * According to a typical trajectory for the introduction and adoption of new technologies









Summary Ph.D. at KI conference doctoral workshop 2021 Interdisciplinary research AI for business

Overarching RQ: **How** to **utilize** the **potential of Al and ML in procurement**? Focus on **OM community** with **intersection** to **information systems**

#1 Case study TCO prediction (How?)

#2 Review+
Procurement
versus sales
(Why?)

#3 Model Simulation optimization (How?)

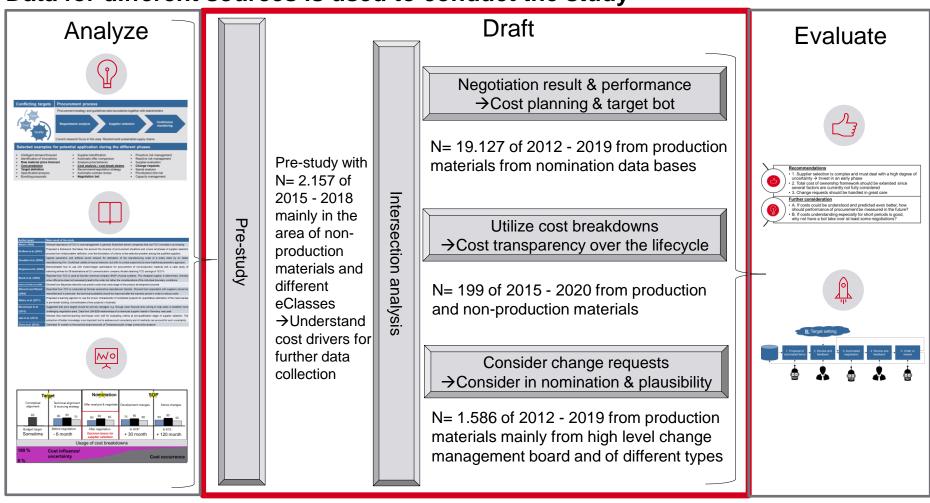
#2 Review Describe the current body of knowledge highlighting the potential (What?)

Ph.D. summary presented at HICL DC ©



Study I framework for TCO analysis case study

Data for different sources is used to conduct the study



Data from different sources, use cases, and types based on a pre-study.

Note: Due to time restrictions, the presentation has been optimized for the format, four further slides are included in the deck and further details are included in the working draft.





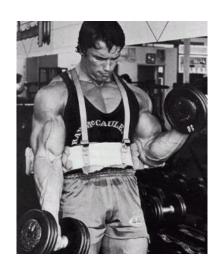
Study I case study results of cost prediction quality Mean, standard deviation (SD), and mean magnitude relative error (MMRE)

Data has been split into 70 % training and 30 % test set

| Data set | Naïve baseline | | Logistic | | | Regression | | | Bayesian | | | |
|--------------|----------------|-----|------------|------|-------|------------|------|--------------|----------|-------|-----|------|
| | | | regression | | trees | | | optimization | | | | |
| | Mean | SD | MMRE | Mean | SD | MMRE | Mean | SD | MMRE | Mean | SD | MMRE |
| Intersection | -3.2 | 6.4 | 32 % | -4.0 | 3.7 | 21 % | -3.7 | 2.6 | 17 % | - 3.6 | 2.2 | 12 % |

Next steps:

- 1. Train and optimize models, e.g. bagging or boosting
- Compare with others methods and studies, i.e. 25 % MMRE considered good for early software cost estimation
- 3. Plug the results back in the TCO equation



Al models perform well, at least compared with baseline and regression.







Study II literature review AI and ML methods in procurement Overview of the study

Background

Al and ML techniques are recently starting to emerge in procurement theory and practice worldwide.

Based on literature reviews of big data analytics in supply chain management, there is a need to review the literature focusing specifically on artificial intelligence and machine learning in procurement.

The work started off as a systematic literature and become more of a conceptual literature review over time.

Methodology

Content analysis approach by **Mayring**:

- 1. **Material collection**, which entails a process of search and delimitation of articles
- 2. **Descriptive analysis**, which provides characteristics of the studied literature
- 3. **Category selection**, which aims to construct a classification framework

Followed by the material evaluation, additionally 20 expert interviews conducted to assess the business value and the ease of implementation.

Results

210 publications were identified, described and classified based on the strategic, tactical and operational level of procurement and according to the ACM computing classification system.

Summarized the state-of-theart in theory enriched with practical ideas, made available for further research.

11 use case clusters were derived, assessed through the interviews, and a research agenda is proposed.



Understanding of the state-of-the art and highlight research opportunities.

Sources: ACM, 2012, Waller and Fawcett, 2013, Mayring, 2014, Souza, 2014, Nowosel et al., 2015, Gunasekaran et al., 2017, Nguyen et al., 2017, Vollmer et al., 2018.









Study II literature review, application, and future research Other reviews and gaps

| Classification | | SCOR framework | | | | | | | | |
|--|---|---|---|---|---------|--------|--------|--|--|--|
| | | Plan | Source | Make | Deliver | Return | Enable | | | |
| CCS framework (Note: Most other reviews in supply chain literature use the broad terminology | AI/ ML methods | | [Application focus] Strategic, tactical and operational of procurement: Spreitzenbarth et al., 2021 and [impact focus] Guida et al., 2021 and Allal-Chérif et al., 2021 | For instance For instance Li et al., Woschank et al., 2017 2020 | | | | | | |
| | | For instance Min, 2010, Kobbacy and Vadera, 2011, The Economist, 2019, Brintrup, 2021 | | | | | | | | |
| of big data analytics) | Others For instance Waller and Facett, 2013, Hazen et al., 2014, Schoenherr and Speier-Pero | | | | | | | | | |
| Other | | | | | | | | | | |

This work contributes to the understanding of AI and ML in operations management from theory and practical insights providing further research directions and provides an overview to supply managers looking for guidance. ACM frameworks offer a clear terminology as de-facto standard in information technology providing stronger clarity.

The methodology with SCOR and ACM can be applied in other reviews.

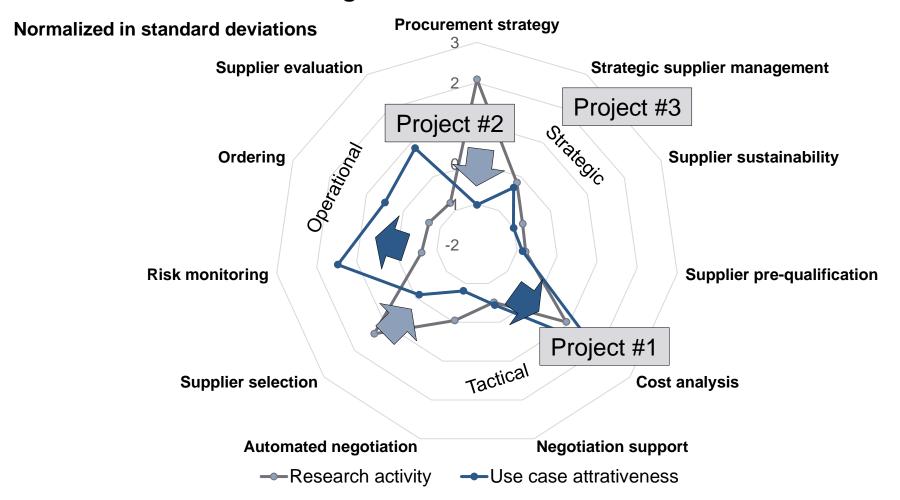








Study II comparison of research activity and attractiveness There is mismatch but also alignment



Focus on cost analysis and operational use cases.







Study II extension the state of AI procurement vs sales Potential academic master thesis is cooperation with Mannheim marketing chair

Research question: Why is procurement lagging in Al adoption versus sales?

| Dimension | Procuren | nent | Sales | | | |
|-------------|---------------------|---------------|-------------------|-----------------|--|--|
| Difficusion | Decisions | Data | Decisions | Data | | |
| Strategic | Value network | Overall costs | Value proposition | Overall profits | | |
| | value Helwork | and quality | value proposition | and revenue | | |
| Tactical | Supplier coloction | Achieved | Project bidding | Achieved | | |
| | Supplier selection | Savings | Project bluding | projects | | |
| Operational | Supplier evaluation | Performance | Drainat control | Performance | | |
| | Supplier evaluation | measurement | Project control | measurement | | |

→Building on the review of AI and ML in procurement presented at the IPSERA 2021, conduct comparative study, interesting master thesis topic. Consider strategic goals, potentially another MT focusing on the cross-functional potential of AI use cases ©

Provide ideas and suggestions on how procurement could speed up.







Study III overview of how to solve the sizing problem Optimize value creation of procurement through simulation as a work system

Research question: How to optimize procurement value creation through simulation?

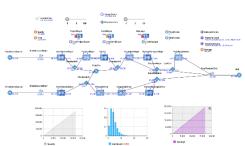
Preposition I: The sizing problem can be solved by optimizing the value function Preposition II: Simulation shows flexibility value, e.g., through lean and agile principles Dynamic system with feedback loops

Theoretical background

Output Processing "Value proposition" "Value creation "Delivery system" (TIM)

Internal External Fluctuating: stakeholdersstakeholders - Total spend - Diversity of requisitions Manager - Organizational priorities Indicators: Maverick buying With different Unmet expectations Lead number and types Attitude towards buyer buyer of agents with procurement variable skill and Idle time and support system excessive workload Special function Automated function

Results of case study



Real data to model and train the agents

Simulation as research method

Interesting opportunity for a technical and business oriented master thesis ©



Design a prototype of a simulation-based procurement workflow system.





Summary with questions for discussion Looking forward to your feedback

Summary of the three Ph.D. projects

- #1 Case study: Improve TCO prediction and understanding
- #2 Review+: Describe status quo and highlight the potential
- **#3 Model:** Solve organizational sizing with digital twin simulation



Questions for discussion

- **Value:** Where do you see the most value for future research and practical application? What do you suggest to focus on in the design of the Ph.D.?
- **Novelty:** Which relevant works and theories would you recommend to investigate further?
- **Method:** Where do you see shortcomings? What would you do differently?

Looking forward to an interesting discussion!





Thanks for your time! The references are summarized below.

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