Case research and design science ... 
... as research paradigms for statistical engineering?

Jeroen de Mast

Jeroen de Mast
Professor, University of Waterloo
Academic Director, Jheronimus Academy of Data Science (JADS)
Scientific Director, Holland Innovative

jdemast@uwaterloo.ca

This material is the intellectual property of the author.
This material is provided to you for personal use only. Sharing, posting or selling is strictly forbidden without permission from the author.
Why this talk?

Case studies published in journals

- Potentially ...
  - Rich source of information about the challenges of applying statistics to solve real, messy, complex problems

- But often ...
  - Not many lessons being articulated
  - No reflection on whether these lessons can be generalized
  - No attempts to integrate lessons learned into more coherent new theory

Not-so-useful case study

Six Sigma project report

1. Objective
   We did an interesting project. The goal is to improve a production process.

2. Case description
   We applied some factorial designs, and fitted some regression and ANOVA models. From these we found valuable process improvements.

3. Conclusions
   The new process settings saved the company lots of money.

What did we learn?
What lessons can we generalize?
How does this help to build a body-of-knowledge about applying statistics?
Better-but-still-not-there case study

CASE REPORT

Statistical reasoning in diagnostic probability measurements

Jeroen de Mast, Stefan H. Steiner, Rick Kuijten, and

Research question (as opposed to goals in the case)

Our purpose in presenting and discussing this case is to demonstrate the roles that statistical thinking can play in diagnostic problem-solving, and identify reasoning patterns that make the application of statistical techniques powerful.

Description of what we did to solve the case

Conclusions for the case

Discussion and analysis

Conclusions in the flow-rate case

Based on statistical analysis, we have been able to eliminate many potential causes of the discrepancies.

Statistical reasoning patterns and conclusions

This article is more about statistical reasoning than about solving the specific problem.

Hypothesis generation, testing, and evaluation

- Principle: Instead of blindly testing, consider
- Branch-and-prune strategy
- Principle: When the search space is complex,

Lessons learned for applied statistics

Cases as a research strategy to build a body-of-knowledge about applying statistics to solve problems.

Why this talk?

Purpose of this talk
Propose a framework for case study research ...
... to help SE build a body-of-knowledge about applying statistics to solve complex unstructured problems.

Design Science Research has the potential to offer such framework.

ISEA website:
“To advance insertion into academic curricula and to enhance the professional qualifications and standing among its members”

Talented young people will go elsewhere unless SE has credibility and standing in Academia

2nd purpose of this talk
Present Design Science Research as a potential and strong foundation for SE, that is recognizable to the wider academic community ...
... to help SE gain credibility in the wider academic community.
What is design science, and how does SE fit in?

What is design science?

Main research strategy in applied sciences
- Engineering
- Medicine: “evidence-based medicine”
- Now being adopted by business schools

Conducting and publishing design science research. Inaugural essay of the design science department of the Journal of Operations Management.

1.2. DSR can be regarded as an engineering approach to OM

DSR in operations management can be regarded as a conscientious transfer of the strategy used in engineering research, taking into account the fundamental differences between designing and
What is design science?

Main research strategy in applied sciences
- Engineering
- Medicine: “evidence-based medicine”
- Now being adopted by business schools

Roots in the work of Herbert Simon
- Book: *The Sciences of the Artificial*
- Framework for sciences not so much seeking *truth* but seeking *actionable knowledge*
  - How to build a bridge?
  - How to cure a patient?
  - How to solve a problem?
- “Means/end” thinking

---

Explanatory, formal and design science

**Explanatory sciences**
*Physics, biology, psychology, …*
- Discover laws of nature
- *How*: empirical studies
- *Goal*: truth finding

**Formal sciences**
*Mathematics, logic*
- Develop logical framework for reasoning
- *How*: logical deductions
- *Goal*: logical consistency

**Design sciences**
*Engineering, medicine, management science, …*
- Discover actionable knowledge: techniques, methods, approaches, strategies, principles, …
- ... as a means to achieve an end
- *Goal*: effectiveness (“it works”)
**Design science produces actionable knowledge**

Product of design science research: **prescriptions**
- Methods, techniques, protocols, strategies, analysis templates, reasoning patterns

Generic form:
- In a context $C$
- this approach $A$
- is likely to result in outcome $O$
- which we can understand as the effect of the working mechanisms $M$

*Denyer et al. (2008); Van Aken et al. (2016)*

---

### Sources of knowledge: 1. *Science*

1. Scientific knowledge
   - Mathematical statistics
     - Framework for inferences from data (estimation, hypothesis testing, …)
   - Machine learning and AI
     - Algorithms for (mainly) predictive analytics
   - Problem structuring and problem solving
     - Diagnostic problem solving, creative problem solving, structuring messy problems, …
     - DMAIC, CRISP-DM, pyramid principle, mess maps, …
   - Organizational and management theory
     - Project-mgt, leadership, influencing skills & winning support, organizational development, getting things done, …
Sources of knowledge: 2. cases

2. Experiential knowledge
- Learn lessons from earlier applications: “case-based reasoning”
- Case studies!
- Better for dealing with the messier, unstructured challenges of practical statistics that cannot be understood from formal mathematics

Case-study research

How to learn from case studies?
Case-study research in Management

Guidelines for case-study research in Management:

- Research question
  (what does the researcher hope to learn from the case?)
- Motivation that a case study is the right research method
- Unit of analysis
- Literature review of relevant theory
  -> This yields working hypotheses related to the research question
  - Helps to make the research question more specific, as a choice between alternative hypotheses
  - Helps to determine what observations are needed
- Selection of case or cases
- Systematic collection and documentation of observations
- Within-case analysis
- Cross-case analysis
- Findings and conclusions

Case-study research in Management

The problem of appointment scheduling in outpatient clinics:
A multiple case study of clinical practice

Alex H. Krüger*†, Jeroen de Man*‡, Michel Mandjes*§

Mathematical definition of problem as trade-off between idle times and waiting times

\[(t_1, t_2, \ldots, t_n) = \]

Does mathematical problem definition make sense in clinical practice? Are we solving the right problem?

Extensive literature review → interview questions

- Idle time irrelevant
- Complex constraints and large variety
- No optimization, but flexible adjustment

Selection of 10 cases (clinics)

<table>
<thead>
<tr>
<th>Case</th>
<th>Specialty</th>
<th>Clinicians</th>
</tr>
</thead>
<tbody>
<tr>
<td>1</td>
<td>Internal medicine</td>
<td>27</td>
</tr>
<tr>
<td>2</td>
<td>Orthopedics</td>
<td>2</td>
</tr>
<tr>
<td>3</td>
<td>Endoscopy</td>
<td>11</td>
</tr>
<tr>
<td>4</td>
<td>Psychiatry</td>
<td>20</td>
</tr>
<tr>
<td>5</td>
<td>Orthopedics</td>
<td>26</td>
</tr>
<tr>
<td>6</td>
<td>Otorhinolaryngology</td>
<td>10</td>
</tr>
<tr>
<td>7</td>
<td>Ophthalmology</td>
<td>7</td>
</tr>
<tr>
<td>8</td>
<td>Ophthalmology</td>
<td>33</td>
</tr>
<tr>
<td>9</td>
<td>Neurology</td>
<td>14</td>
</tr>
<tr>
<td>10</td>
<td>Orthopedics</td>
<td>10</td>
</tr>
</tbody>
</table>

Does mathematical problem definition make sense in clinical practice?
Are we solving the right problem?

Extensive literature review → interview questions

- Idle time irrelevant
- Complex constraints and large variety
- No optimization, but flexible adjustment

Case studies in SE

Proposed structure for case studies in SE:

Research question
What generalizable lessons for SE do we hope to learn?

Presentation of the case(s)

Discussion of the case
- Explicate
- Validate
- Understand
- Generalize

... lessons learned
Case studies in SE

Discussion of the case:

- **Explicate**
  Articulate what the applied approach was

- **Validate**
  Critically evaluate how effective the chosen approach really was.
  - What was the desired outcome, and to what extent was it achieved?

- **Understand**
  Try to explain the approach’s effectiveness from results from mathematics or other sciences
  - What are the working mechanisms of the approach?

- **Generalize**
  Discuss in what situations the approach could or could not be effective?
  - How generalizable is the approach?

Denyer et al. (2008); Van Aken et al. (2016)

---

Case studies in SE

Proposed structure for case studies in SE:

- **Research question**
  What generalizable lessons for SE do we hope to learn?

- **Literature**
  What’s already known in scientific literature?

- **Presentation of the case(s)**

- **Discussion of the case**
  - Explicate
  - Validate
  - Understand
  - Generalize

... lessons learned

Result:

“In a context $C$, this approach $A$ is likely to result in outcome $O$, which we can understand as the effect of the working mechanisms $M$.”
Applied sciences as autonomous knowledge domains

Is applied science equally respectable as theoretical science?

Is SE just applied mathematical statistics?

Sociology is just applied psychology. Psychology is just applied biology. Biology is just applied chemistry. Which is just applied physics. It's nice to be on top. Oh, hey, I don't see you guys all the way over there.
Engineering is just applied physics?

Herbert Simon
- Fed up with scorn of theoretical scientists
- Wrote *The Sciences of the Artificial* to explain the relation between applied and theoretical science.

Two domains of knowledge

- Understand internal working of tools
- Understand functional use of tools

Two domains of knowledge: cars ...

Under the hood
- Understand car’s internal working
- Laws of mechanics, electronics

From behind the steering wheel
- Understand a car’s functional use
  - Traffic rules, driving skills, motor skills, knowledge of functions of pedals and meaning of indicator lights, ...

The functional use of a car, and its internal working, are two disjoint domains of knowledge. Mechanics and electronics do not help much in learning how to use a car.
Tools in isolation vs. as purposive system

Laws of physics

Laws of biology, psychology, sociology, ...

Very complex, very diverse

Task environment

Design sciences are about interaction between user, tool and task environment
• What sort of purposes do users have?
• What sort of environments are there?
• What tool would be effective for those purposes in those environments?

Engineering is just applied physics?

• A car understood purely from laws of physics is but a purposeless metal object with rubber, plastics and copper wire.

• Understand a car as a functional tool for a user with purposes within a variety of task environments
  • Does not make sense to design a car without knowledge about driving behavior and challenges, traffic rules, ergonomics, etc.
  • Does not make sense to limit driving lessons to the internal working of cars (mechanics and electronics)

• Engineering uses physics, but is much more!
SE is just applied mathematics?

The internal logic and algorithmics of statistical techniques

Mathematical stats. (deductive logic)

The logic of their functional application in inquiry, decision making and problem-solving

Stat. engineering (means/end logic)

- User:
  - What sort of goals in empirical inquiry, decision making, problem solving? *(delicate point: many mathematicians have no first-hand experience with empirical inquiry)*

- Task environment:
  - What sort of challenges, practical complications, issues, ... do users encounter when applying statistics?
  - Which tools are effective for those purposes in those environments?

Example: normality tests

Normality tests ...

- Mathematical logic:
  - Inferential framework for rejecting or not rejecting $H_0$: normality
  - How to define optimal test statistic and calculate $p$-value

```graph
\begin{align*}
p &= 0.000 \\
p &= 0.000 \\
\end{align*}
```
Example: normality tests

Normality tests ...

- **Mathematical logic:**
  - Inferential framework for rejecting or not rejecting $H_0$: normality
  - How to define optimal test statistic and calculate $p$-value

- **Statistical engineering logic:**
  - $H_0$ usually implausible on a priori grounds

More interesting questions:
- Is the normal distribution a useful approximation? How can you tell?
- What kind of departures from normality are there? (outliers, multimodality, rounded data, skewness, …)
- And how to deal with them in your study? (data cleaning, transformation, other probability distribution, nonparametrics, …)

Take-aways

- **Case-study research** is useful for building a body-of-knowledge about statistical engineering
  - Detail-rich, empirical sources of knowledge about realistic challenges in applied statistics and problem solving
  - Opportunities to learn about what does and doesn’t work in the complex and messy world of application
  - But ... lessons in cases should be explicated, validated, understood and generalized ...
    otherwise we end up with little but an enumeration of case descriptions, but without generalizable lessons and a growing body-of-knowledge

- **The art of applying statistics** in inquiry, decision-making and problem-solving merits scientific study in itself
  - “Statistical engineering”
  - Altogether different knowledge domain than mathematical statistics
  - Answers questions of the form: In which contexts and for what outcomes are which approaches effective?