

The Literature Review Seminar

Steps of the process

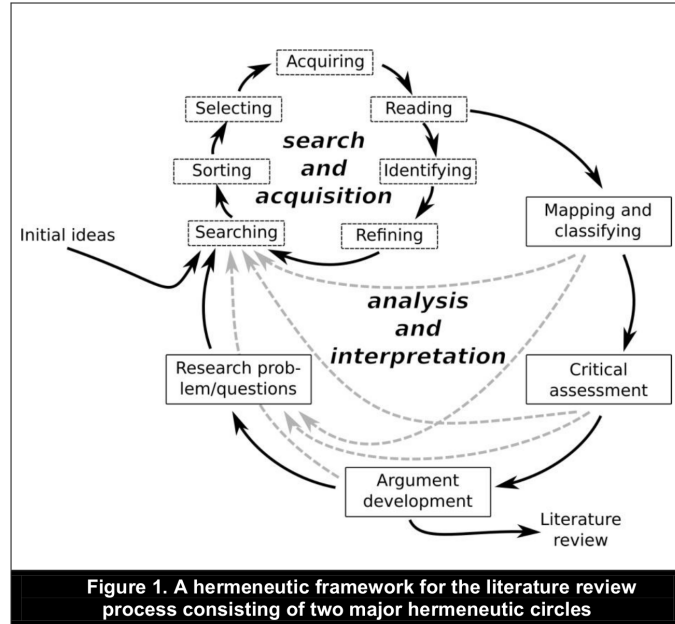
- Understand the generic steps of the review process
- Appreciate the critical methodological choices in the search, screen, and analysis

What are the generic steps of a literature review?

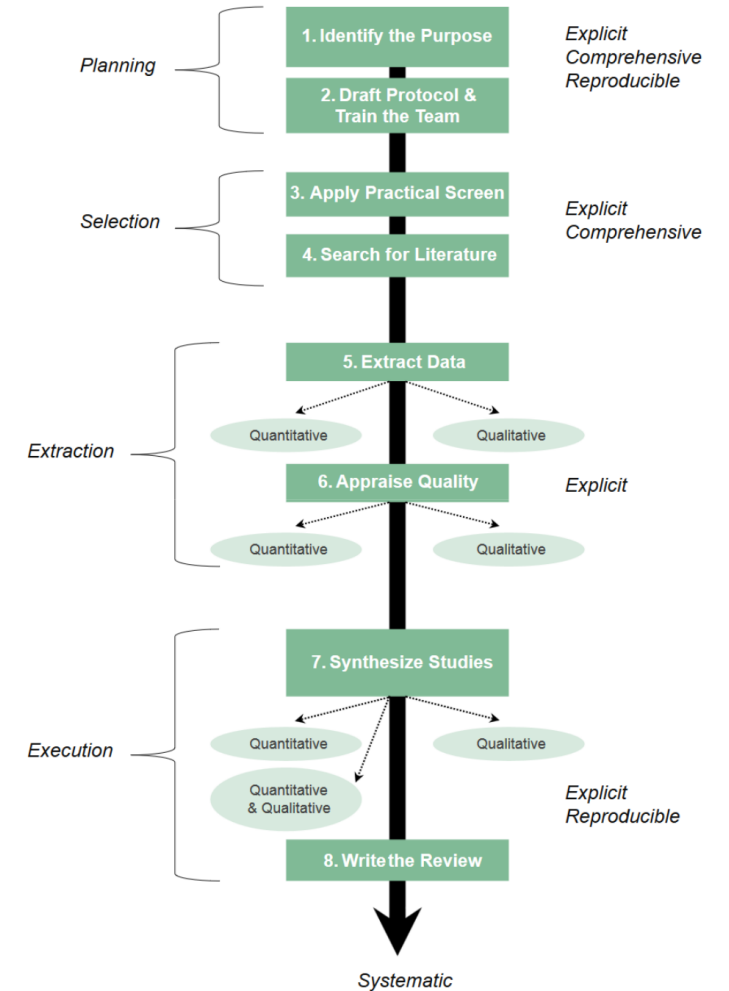


 **Task:** Outline the steps of the literature review process as you envision them.

Generic steps: Examples



- The hermeneutic framework of Boell and Cecez-Kecmanovic (2014) vs.
- The systematic guide of Okoli (2015)



Generic steps: Templier and Paré (2018)

Table 8. Frequency of reporting items per review type.

	Narrative (n = 25)	Descriptive (n = 22)	Scoping (n = 9)	Critical (n = 16)	Meta-analysis (n = 12)	Qualitative sys- tematic (n = 6)	Theory devel- opment (n = 52)
<i>Step 1: Problem formulation</i>							
Primary goals or research questions	100	100	100	100	100	100	100
Key concepts or theories being investigated	84	91	89	94	100	100	100
<i>Step 2: Literature search</i>							
How the literature search is performed	44	95	89	69	100	100	25
Multiple search strategies			44	19	100	33	13
Multiple publication types			22	13	92	33	17
Comprehensiveness of search & restrictions if applicable		86	78	50	100	83	21
How reputation of the sources is considered	28			63			13
Strategies used to minimise publication bias					25	0	
<i>Step 3: Screening for inclusion</i>							
How primary studies are screened or selected	20	91	67		67	67	21
Results of parallel independent study selection		5	11		8	0	
How studies using the same data-set are treated					25	17	
Flow diagram or description of screening process			11		92	17	

Generic steps: Templier and Paré (2018)

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	Narrative (n = 25)	Descriptive (n = 22)	Scoping (n = 9)	Critical (n = 16)	Meta-analysis (n = 12)	Qualitative sys- tematic (n = 6)	Theory devel- opment (n = 52)
<i>Step 4: Quality assessment</i>							
How quality assess- ment is performed					8	0	
Results of parallel independent assessment					8	0	
<i>Step 5: Data extraction</i>							
Data extraction plan		95	56		92	100	
Tools or methods used to extract data		77	67		83	83	10
Results of parallel in- dependent coding process		41	33		67	67	
<i>Step 6: Data analysis and interpretation</i>							
How data analysis is performed			56		100	83	19
How study quality is considered in interpretation of findings					0	0	
Profile of the included studies		91	67		75	67	
Justification of data analysis methods or techniques			22		100	67	
Methodological limitations	28	41	33	31	67	50	25

Generic steps

Summary

- The **nature of steps varies**, including their labels, their characteristics, and how they are arranged
- The steps **depend on the review type**
- Some steps are more **generic**, while others are more **specific** and only apply to selected types of reviews

In the following, we focus on the steps summarized by Templier and Paré (2018):

1. Problem formulation
2. Literature search
3. Screening for inclusion
4. Quality assessment
5. Data extraction
6. Data analysis and interpretation

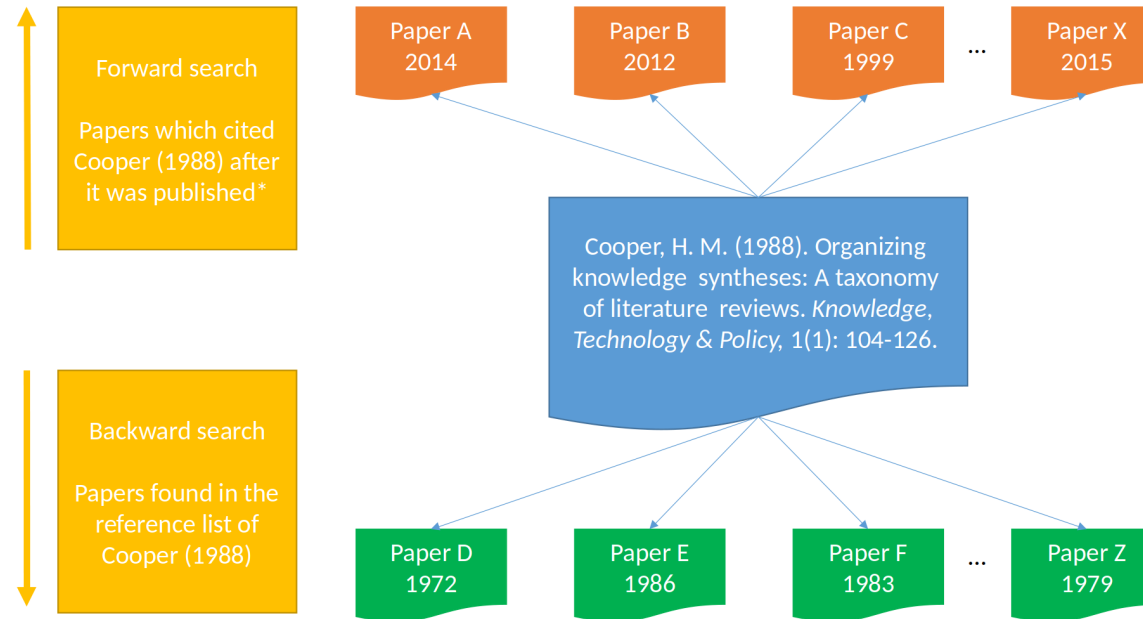
Problem formulation

- Rationale for the review, including an overview of related review papers
- Gap-spotting or problematization (Alvesson and Sandberg 2011):
 - Gap-spotting is seen as (too) common, and may only signify a contribution if the authors can make a convincing argument that the gap is important
 - Problematization, as an approach that challenges existing theory and the underlying assumptions, can lead to more interesting and noteworthy contributions
- Research question or objectives

Literature search: Foundations

- Search types: *Lookup* vs. *exploratory* vs. **systematic search** (Gusenbauer and Haddaway 2021)
- Search scope: time, journals, and academic vs. gray literature
- Search techniques (with associated search sources):
 - Database search (keyword-based)
 - Backward search, i.e., search reference sections to go back in time (aka. snowballing, pearl-growing)
 - Forward search, i.e., using citation indices to go forward in time
 - Table-of-content search (whole journals)
 - Sampling from prior review papers
 - Consulting with peers (e.g., through direct contact or mailing lists)

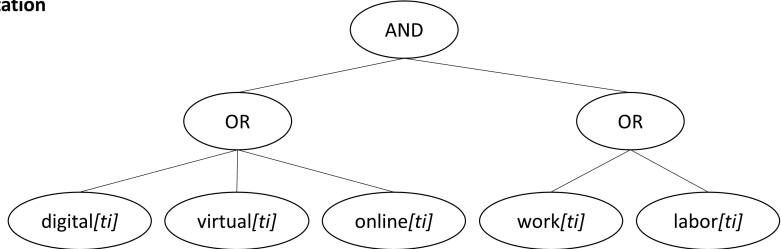
Literature search: Citation searches



* as found in *Web of Science* or *Google Scholar*

Literature search: The database search

- Most common search strategy in the management disciplines (58% according to Hiebl, 2023)
- Common databases: Web of Science, EBSCO Host, ABI Informs, AIS eLibrary, ACM Digital Library, IEEEXplore, etc. (Knackstedt and Winkelmann 2006, Hiebl 2023)
- Effective search strategies for database searches combine search terms with Boolean operators

String representation	(digital OR virtual OR online) AND (work OR labor) <i>[in title field]</i>																
Tree representation																	
List representation	<table border="1"> <tr><td>1</td><td>digital [ti]</td></tr> <tr><td>2</td><td>virtual [ti]</td></tr> <tr><td>3</td><td>online [ti]</td></tr> <tr><td>4</td><td>1 OR 2 OR 3</td></tr> <tr><td>5</td><td>work [ti]</td></tr> <tr><td>6</td><td>labor [ti]</td></tr> <tr><td>7</td><td>5 OR 6</td></tr> <tr><td>8</td><td>4 AND 7</td></tr> </table>	1	digital [ti]	2	virtual [ti]	3	online [ti]	4	1 OR 2 OR 3	5	work [ti]	6	labor [ti]	7	5 OR 6	8	4 AND 7
1	digital [ti]																
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Literature search: The "building-blocks" approach

- RQ: What factors do influence physicians' acceptance of telemedicine?

	Concept 1	AND	Concept 2	AND	Concept 3
	Telemedicine		Physician		Acceptance
OR	Telehealth		Doctor		Adoption
OR	Teleconsultation		Clinician		Resistance
OR	Tele-expertise				
OR					
OR					
OR					
OR					

Resulting search string: (telemedicine OR telehealth OR ...) AND (physician OR doctor OR ...) AND (adoption OR acceptance OR resistance OR ...)

Building blocks can be based on established frameworks like PICO (population-intervention-control-outcome)

Exercise: Reviewing a search strategy

Imagine you serve as a reviewer for a conference. You review a paper on algorithmic decision-making, along with Table 2.


 **Task:** Evaluate the proposed search strategy critically, taking into account the building-block approach. Make a recommendation to accept, revise, or reject.

Table 2
Search terms.

Themes of search term: algorithm, artificial intelligence, and machine learning; decision, advice, recommendation, and decision aid

ID	Search syntax	Total hits	Ultimately retained**
1	Algorithm* Aversion	840	16
2	Algorithm* Appreciation	788	3
3	(AI OR "Artificial Intelligence") AND Aversion	162	2
4	(AI OR "Artificial Intelligence") AND Appreciation	197	–
5	"AI recommendation" OR "Artificial intelligence recommendation" OR "Algorithm* recommendations" OR "Machine Learning recommendation" OR "ML recommendation"	249	1
6	"AI decision*" OR "Artificial intelligence decision*" OR "Algorithm* decision*" OR "Machine Learning decision*" OR "ML decision*"	2009	3
7	"AI Advice" OR "Artificial intelligence Advice" OR "Algorithm* advice" OR "Machine Learning advice" OR "ML advice"	15	3
8	("AI" OR "Artificial intelligence" OR "Algorithm*" OR "Machine Learning" OR "ML") AND "Decision aid"	697	5

* Takes the place of one or more characters in the search term.

** Figures represent the number of studies after completing selection process.

* Note: Example taken from Mahmud, H., Islam, A. N., Ahmed, S. I., & Smolander, K. (2022). What influences algorithmic decision-making? A systematic literature review on algorithm aversion. *Technological Forecasting and Social Change*, 175, 121390.

Literature search: Strengths and shortcomings of database searches

Strengths:

- Relatively efficient (see Wagner et al. 2021, Appendix A3)
- Transparent and reproducible

Shortcomings:

- Keyword searches: rely on exact matches
- Need to be familiar with the vocabulary (check keywords or taxonomies like [MeSH](#) etc.)
- Assumption of controlled scientific vocabulary although disciplines like Information Systems have abandoned corresponding efforts decades ago (Weber 2003)

Literature search: Search metrics

The common objective is to identify all relevant papers. Literature searches retrieve documents:


	Relevant	Not relevant	
Retrieved	True positive	False positive	
Not retrieved	False negative	True negative	unknown

Three key metrics are particularly relevant in the context of literature searches (Cooper et al. 2018):

1. **Sensitivity** aka. recall: $TP / (TP + FN)$. How many of the relevant papers do we find? ?
2. **Specificity**: $TN / (TN + FP)$. How well does the search exclude irrelevant results? ?
3. **Precision**: $TP / (TP + FP)$. How many of the search results are actually relevant?

Literature search: Assessing searches

- **Precision** is the only metric that can be measured in a typical literature review
- A **highly precise search strategy should be suspicious** because the search may not be comprehensive enough
- Based on the **SYNERGY** dataset, average precision is 2% - 4% in medicine, chemistry, and computer science

 **Question:** Would you expect more precise searches in disciplines like Information Systems, Management, or the Social Sciences?

Datasets and variables [↗](#)

The SYNERGY dataset comprises the study selection of 26 systematic reviews. The dataset contains 169,288 records of which 2,834 records are manually labeled as inclusion by the authors of the systematic review. The list of systematic review and basic properties:

Nr	Dataset	Topic(s)	Records	Included	%
1	Appenzeller-Herzog_2019	Medicine	2873	26	0.9
2	Bos_2018	Medicine	4878	10	0.2
3	Brouwer_2019	Psychology, Medicine	38114	62	0.2
4	Chou_2003	Medicine	1908	15	0.8
5	Chou_2004	Medicine	1630	9	0.6
6	Donners_2021	Medicine	258	15	5.8
7	Hall_2012	Computer science	8793	104	1.2
8	Jeyaraman_2020	Medicine	1175	96	8.2
9	Leenaars_2019	Psychology, Chemistry, Medicine	5812	17	0.3

Literature search: Application

- Draft a search strategy for your topic, following the building-blocks approach.

Concepts →

Synonyms ↓

- Does the building block approach provide a good fit with your context?

Literature search: Outlook

Open challenge:

- How can we iterate efficiently?
- How do we justify the decision to terminate a search?
- How can we use evidence to search effectively?
- How can we make progress without database providers?



Screen

- The screen is typically completed in two parts:
 - A pre-screen based on metadata ("*include if in doubt*")
 - A screen based on full-text documents, resulting in the final sample
- The screen is often based on explicit inclusion and exclusion criteria

Study Selection

Studies were included if (1) a randomized controlled trial (RCT) design was used, (2) the intervention involved using a Fitbit device to improve PA and/or other health-related outcomes (eg, weight loss), and (3) the study reported outcomes related to healthy lifestyle measures (eg, steps, MVPA, weight, and BMI). Only peer-reviewed journal and conference papers were considered.

Articles were screened in a two-step process. First, all titles and abstracts were examined by one author (MR). Any citations that clearly did not meet the inclusion criteria were excluded. Second, all abstracts and full-text articles were examined independently by two authors (MR and GW). Any disagreements in the selection process were resolved through discussion with a third author (GP or SK).

Screening reliability

Screening tasks are often split among the review team to complete the process **more quickly**, and to ensure **reliable decisions**.

Process:

1. Definition of criteria, training, and pilot test
2. Parallel-independent screen (partially or fully overlapping sample)
3. Independent screen of the remaining papers (if any)
4. Reconciliation: in case of disagreements, final decisions are made by selected team members (often more senior researchers)
5. Calculate inter-rater agreement (e.g., Cohen's Kappa) and report the process

Interpretation of Kappa Values

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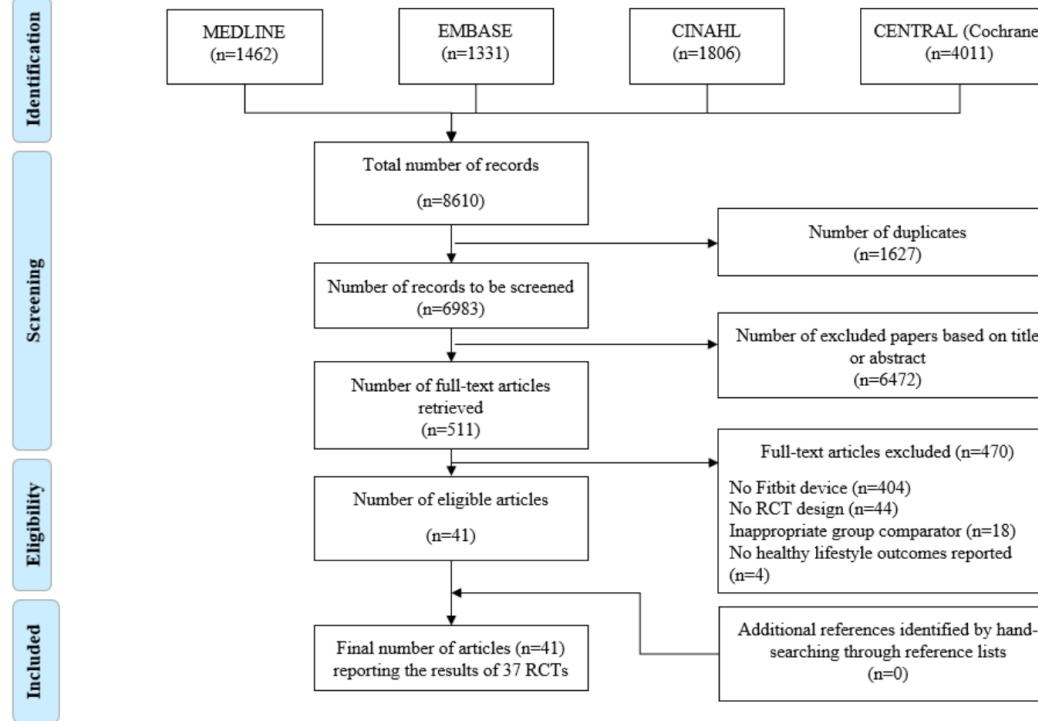
Kappa Value Range	Interpretation
≤ 0	No agreement
0.01 – 0.20	None to slight
0.21 – 0.40	Fair
0.41 – 0.60	Moderate
0.61 – 0.80	Substantial
0.81 – 1.00	Almost perfect agreement

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Note: When data is skewed—meaning one category is much more common than others—the Kappa statistic can be artificially low even if there is a high level of agreement. This occurs because Kappa adjusts for the level of agreement that would be expected purely by chance. In skewed distributions, the expected chance agreement tends to be high, which lowers the Kappa score. Essentially, in skewed distributions, even a relatively high observed agreement may not lead to a high Kappa, as the metric accounts for the imbalance.

Reporting the search and screen

Figure 1. Flow diagram. RCT: randomized controlled trial.



The PRISMA flow chart (updated version by Tricco et al. 2018)

An online version is available [here](#)


Break



Reading strategies

The reading activities can be organized strategically at two levels:

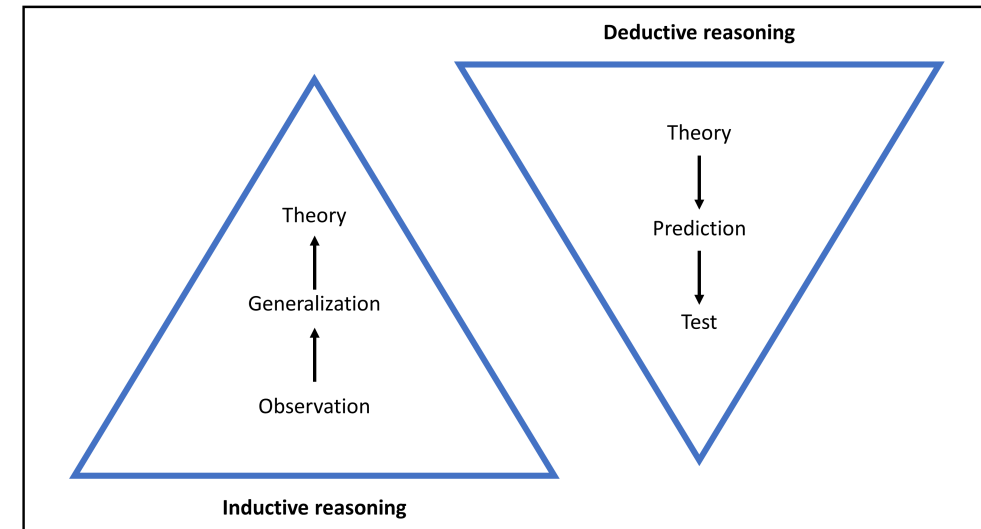
- The overall corpus level: In which order should papers be read or skimmed?
- The individual paper level: How should the different parts of a paper be read?

 **Question:** Assume you have 300 papers to cover, how would you organize the reading activities?

Data analysis

Key differences with regard to data extraction and analysis:

- Focus on metadata vs content
- Inductive vs deductive reasoning



Data analysis example: Metadata profiling (example)

Table A.2
Frequency table.

Journals and conferences	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020	Sum
Decision Support Systems	-	1	-	-	1	-	-	-	1	-	-	-	-	3
e-Service Journal	-	1	-	-	-	-	-	-	-	-	-	-	-	1
Electronic Markets	-	-	-	-	-	-	-	-	-	-	-	1	-	1
Information & Management	-	-	-	-	-	-	-	1	-	-	-	-	-	1
Information Systems Frontiers	-	-	-	-	-	-	-	1	-	1	-	-	1	3
Information Systems Journal	-	-	-	-	-	-	-	-	-	-	-	2	-	2
Information Systems Research	-	-	-	-	-	-	-	-	1	1	1	-	1	4
International Journal of Electronic Commerce	-	-	-	-	-	-	-	-	-	-	-	-	1	1
Journal of Management Information Systems	-	-	-	-	-	-	-	-	-	-	1	-	-	1
MIS Quarterly	1	-	-	-	-	-	-	-	-	-	-	-	-	1
MIS Quarterly Executive	-	-	-	-	-	-	-	-	-	-	1	-	-	1
The Journal of Strategic Information Systems	-	-	-	-	-	-	-	-	-	1	1	1	-	3
Americas Conference on Information Systems	-	-	-	1	-	-	-	1	-	-	1	1	-	4
European Conference on Information Systems	-	-	-	1	-	-	-	-	-	-	-	1	-	2
Hawaii Int. Conference on System Sciences	-	-	-	-	-	-	-	-	-	1	3	-	-	4
International Conference on Information Systems	-	-	-	-	1	-	2	2	1	2	4	2	*	14
Pacific Asia Conference on Information Systems	-	-	-	-	-	-	-	-	-	1	1	-	1	3
Sum	1	2	-	2	2	-	2	5	3	7	13	8	5	49

Note. *The Proceedings of the 41st International Conference on Information Systems (2020) were not yet available.

Data analysis example: Co-citation analysis

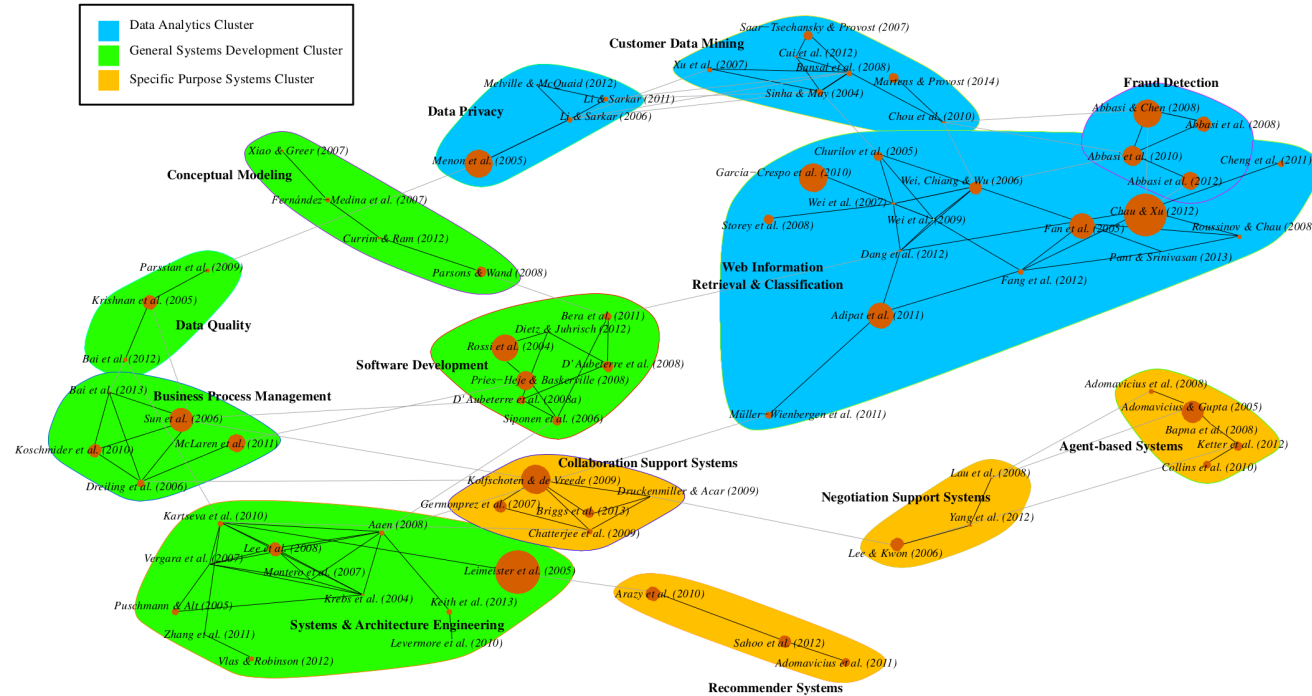
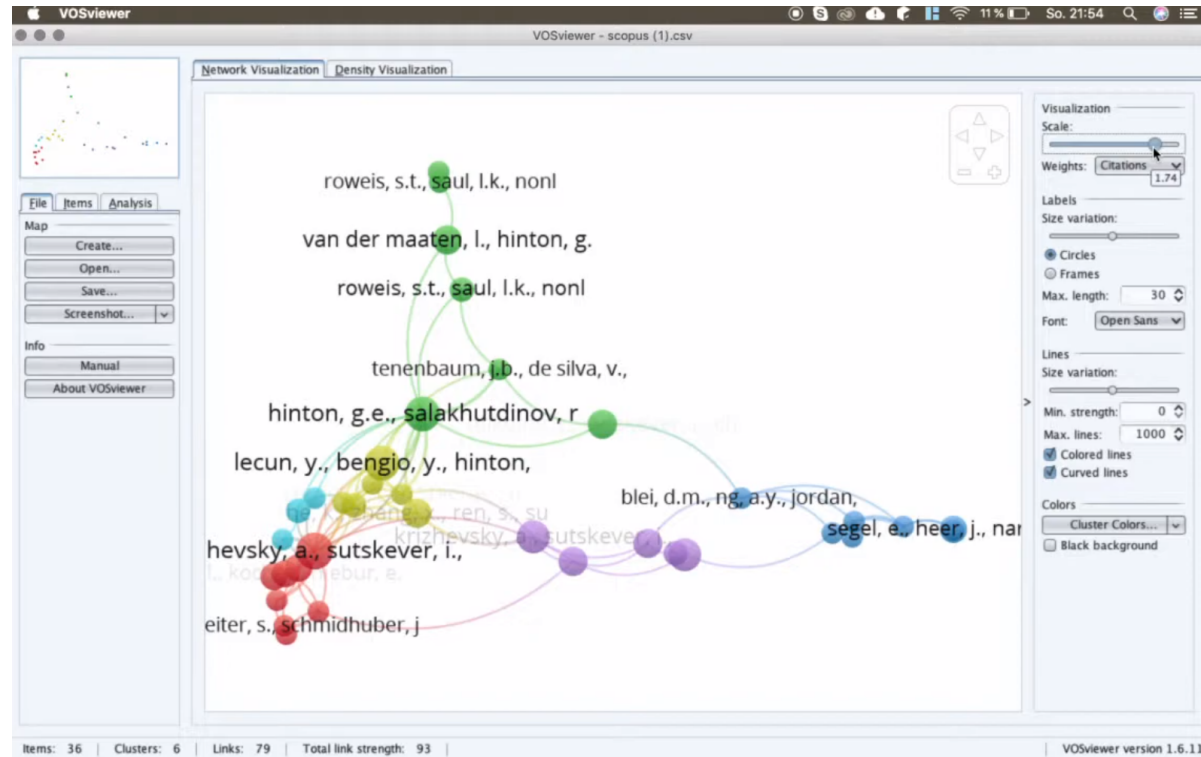


Figure 3. A Map of Impactful IS DSR Papers (2004-2014)

Data analysis example: VOS viewer



- Example keyword analysis: <https://www.youtube.com/watch?v=9dTWkNRxUtw>
- Example bibliometric analysis: <https://www.youtube.com/watch?v=xmLWjcsV4zQ>

Data analysis example: Inductive coding

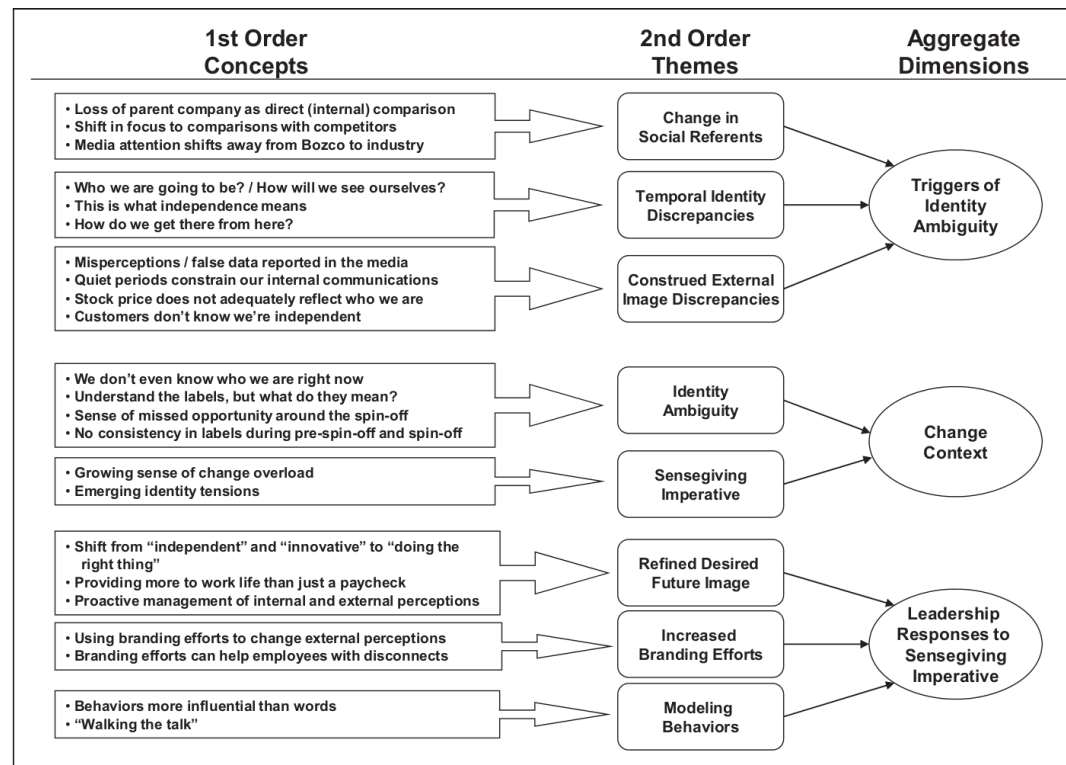
Grounded theory is an inductive method commonly used in literature reviews (Wolfswinkel et al. 2013)

In the data analysis phase, the three coding techniques are central:

- **Open coding** generates higher-abstraction level type categories from sets of concepts/variables
- **Axial coding** develops categories and relates them to their possible sub-categories
- **Selective coding** integrates and refines the categories

Data analysis: The Gioia data structure


The coding process and results are often illustrated in the *Gioia data structure*



Data analysis: Example for inductive analysis

Context:

- Scope: Digital platforms for knowledge-intensive services, such as Upwork, Fiverr, or TopCoder
- Sample: 50 papers, mostly published in the Information Systems discipline
- Data: Text fragments and figures have been pre-selected (see [worksheet](#))

 **Task:** Analyze extant research and inductively develop a process model

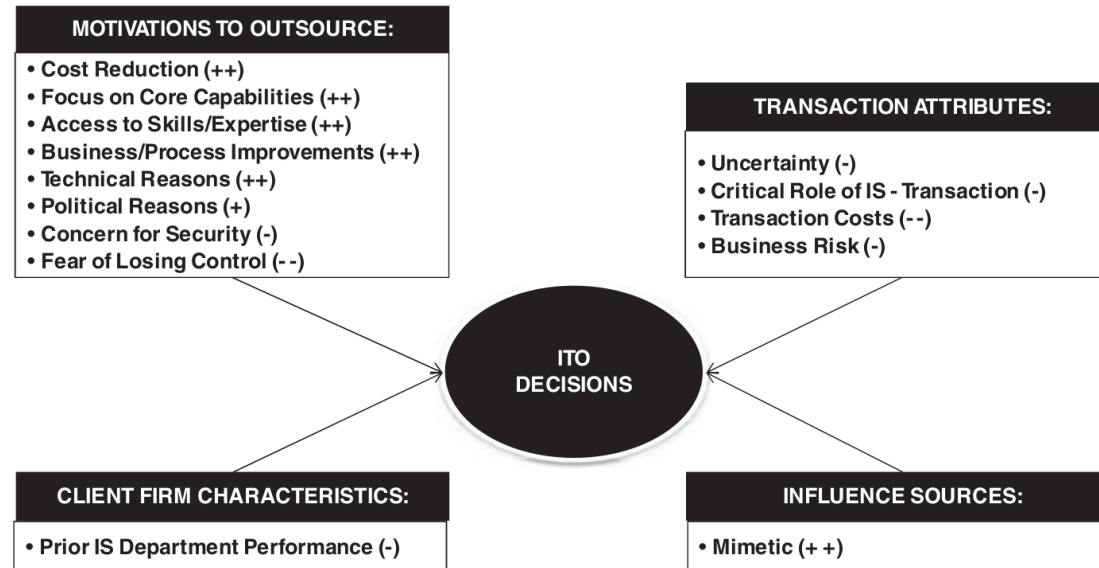
Data analysis example: Aggregating evidence (I)

Vote counting is one technique to aggregate the evidence from prior empirical studies

- Key variables are extracted and compiled in a list of master codes
- Effects between independent and dependent variables are coded:
 - $+1$ for a positive significant effect
 - 0 for no-significant effects
 - -1 for negative significant effects

Example: Lacity et al. (2011)

Effects are aggregated and presented as follows:



LEGEND:

- (++) more than 80% of the evidence is positive and significant
- (+) 60% to 80% of the evidence is positive and significant
- (-) more than 80% of the evidence is negative and significant
- (-) 60% to 80% of the evidence is negative and significant

Data analysis example: Aggregating evidence (II)

Strength of vote counting:

- Aggregates evidence from **quantitative and qualitative studies**

Shortcoming of vote counting:

- Risk of bias is not assessed
- Effect sizes are not determined

Meta-analysis techniques address these shortcomings.

Data analysis: Risk of bias assessment (I)

- Example: Ringeval et al. (2020): "Fitbit-Based Interventions for Healthy Lifestyle Outcomes: Systematic Review and Meta-Analysis"
- The [Cochrane risk-of-bias tool for randomized trials \(RoB 2\)](#) covers seven **domains of bias**, as illustrated in the table

Risk of bias table

Bias	Authors' judgement	Support for judgement
Random sequence generation (selection bias)	Low risk	"[...] using a computer-generated random number schedule of 10 permuted blocks of 6 and the final block of 8." (p. 3)
Allocation concealment (selection bias)	Low risk	"To ensure allocation concealment, randomization to groups was undertaken by a blinded remote investigator (MS) not involved in recruitment [...]" (p.3). It is a central allocation.
Blinding of participants and personnel (performance bias)	High risk	Due to the nature of the intervention and control conditions make blinding impossible.
Blinding of outcome assessment (detection bias)	Low risk	"We conducted a pilot randomized controlled trial with blinded outcome assessment." (p. 2) "Study investigators conducting data collection were blinded to group allocation" (p. 3)
Incomplete outcome data (attrition bias)	Low risk	"Overall, there were 20% of missing data at the 6-month questionnaire follow-up and 16% of missing data across the 6-month weekly surveys." (p. 7). The reasons for missing data are not related to true outcome (p. 7) but they just mentioned they analyzed data by "intention to treat" (p. 6)
Selective reporting (reporting bias)	Low risk	The study protocol is available and all of the study's pre-specified (primary and secondary) outcomes that are of interest in the review have been reported in the pre-specified way.
Other bias	Low risk	The study appears to be free of other sources of bias.

Data analysis: Risk of bias assessment (II)


	Random sequence generation (selection bias)	Allocation concealment (selection bias)	Blinding of participants and personnel (performance bias)	Blinding of outcome assessment (detection bias)	Incomplete outcome data (attrition bias)	Selective reporting (reporting bias)	Other bias
Amorim, 2019	+	+	+	+	+	+	+
Ashe, 2015	+	+	+	+	+	+	+
Azar, 2016	+	+	+	+	+	+	+
Ball, 2016	?	?	?	?	+	+	+
Brown, 2018	+	+	+	+	+	+	+
Cadmus-Bertram, 2019	+	+	+	+	+	+	+

Data analysis: Data extraction

Research objective: "to assess the effects of Fitbit-based interventions, compared with non-wearable control groups, on healthy lifestyle outcomes." (Ringeval et al. 2020)

Outcome of interest:

- Steps per day (control vs. intervention group) at follow-up

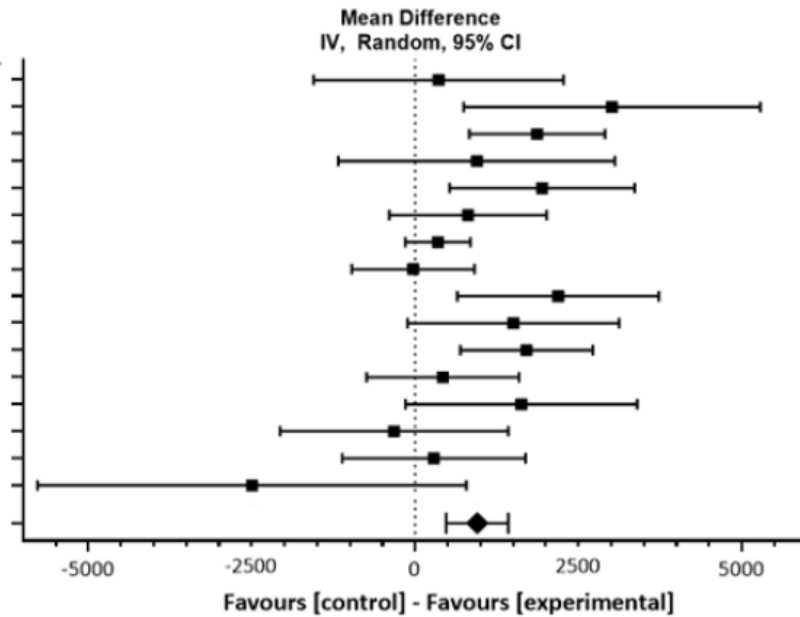
 **Task:** Extract the data from two randomized controlled trials: [Thorndike et al. 2014](#), [van Blarigan et al. 2019](#) based on the following coding sheet:

Study	Intervention group			Control group		
	Steps per day	SD	n	Steps per day	SD	n
Thorndike et al. 2014						
van Blarigan et al. 2019						


Data analysis: Forest plot of standardized mean differences

Study or Subgroup	Experimental			Control			Weight	Mean Difference IV, Random, 95% CI
	Mean	SD	Total	Mean	SD	Total		
Amorim, 2019	7,379.86	3,627	31	7,020.14	3,554.71	24	4.3%	359.72 [-1551.48, 2270.92]
Ashe, 2015	7,606	3,917	12	4,593	663	7	3.3%	3013.00 [743.02, 5282.98]
Cadmus-Bertram, 2019	1,470	1,881	24	-398	1,751	23	8.5%	1868.00 [829.54, 2906.46]
Cheung, 2019	6,608.29	4,169.86	26	5,665.43	2,338.42	11	3.7%	942.86 [-1173.42, 3059.14]
Christiansen, 2019	6,114	1,989	14	4,169	1,890	15	6.3%	1945.00 [530.67, 3359.33]
Duscha, 2018	411	1,836	16	-398	1,225	9	7.4%	809.00 [-395.09, 2013.09]
Finkelstein, 2016	-130	2,601.31	203	-480	2,516.41	201	12.3%	350.00 [-149.07, 849.07]
Hornikx, 2015	984	1,208	12	1,013	1,275	15	9.1%	-29.00 [-968.93, 910.93]
Katz, 2018	1,441	2,829	31	-747	3,064	26	5.7%	2188.00 [645.66, 3730.34]
Li, 2018	8,217.4	3,095.5	30	6,713.6	3,354.3	31	5.4%	1503.80 [-115.22, 3122.82]
Miragall, 2018	7,958	2,005	22	6,251	1,484	26	8.6%	1707.00 [693.43, 2720.57]
Oliveira, 2019	7,010	3,163	46	6,584	2,612	50	7.6%	426.00 [-740.04, 1592.04]
Paxton, 2018	6,917	3,445	22	5,291	2,298	19	4.8%	1626.00 [-146.00, 3398.00]
Simons, 2018	7,741	4,553.55	55	8,061	5,111.59	63	4.9%	-320.00 [-2063.96, 1423.96]
Thorndike, 2014	7,886	3,622	50	7,600	3,492	49	6.3%	286.00 [-1115.39, 1687.39]
Van Blarigan, 2019	10,047	4,461	20	12,541	5,535	17	1.8%	-2494.00 [-5771.98, 783.98]
Total (95% CI)			614			586	100.0%	950.54 [475.89, 1425.18]

Heterogeneity: Tau² = 413106.08; Chi² = 30.69, df = 15 (P = 0.010); I² = 51%
 Test for overall effect: Z = 3.93 (P < 0.0001)



Discussion of the data analysis section

 **Task:** Create a quick draft for the data extraction and analysis section.

- Would you follow an inductive or deductive approach (why)?
- What outcomes would you expect ideally?






We value your feedback and suggestions

We encourage you to share your feedback and suggestions on this slide deck:

[Suggest specific changes by directly modifying the content](https://github.com/digital-work-lab/literature-review-seminar/edit/main/slides/02-steps.md)

[Provide feedback by submitting an issue](https://github.com/digital-work-lab/literature-review-seminar/issues/new)

Your feedback plays a crucial role in helping us align with our core goals of **impact in research, teaching, and practice**. By contributing your suggestions, you help us further our commitment to **rigor, openness** and **participation**. Together, we can continuously enhance our work by contributing to **continuous learning** and collaboration across our community.

Visit this [page](https://digital-work-lab.github.io/handbook/docs/10-lab/10_processes/10.01.goals.html) to learn more about our goals:      .

References

Generic steps

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