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Doctoral Course Management

230329

Decision - Learning

Jan Lindvall

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Point of Departure. :
Models/Algorithms/Frames/Frameworks

“The study of decision making is, in many ways, the study of **search and attention**”.

March (1993, p 23) *A Primer On Decision Making. How Decisions Happen*

System 1 (“Fast, intuitive, gut-feeling”) System 2 (“Slow/Analytical”) Social Norms!

Connections to Learning & Memory (Data Base)

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A Step Back: Two Philosphical streams

Consequentialism: Utilitarianism Bentham, Mill

"Nature has placed mankind under the governance of two sovereign masters, **pain and pleasure**. It is for them alone to point out what we ought to do, as well as to determine what we shall do."

Calculation!

Jeremy Bentham 1748-1832

Deontological view:

Kant Categorical Imperative.

"It is our duty to act in such a manner that **we would want** everyone else to act in a similar manner in similar circumstances towards all other people. **Act according to the maxim that you would wish all other rational people to follow, as if it were a universal law**."

- The Trolley Problem

Immanuel Kant 1724-1804

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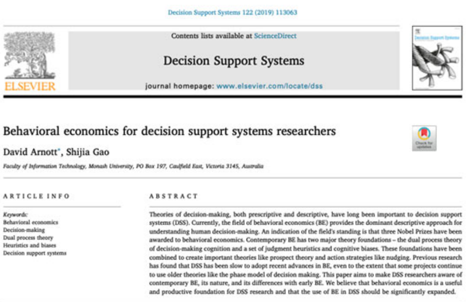
Decision making (process?)

Theories- **Ideas** ("Socio", Social")



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Behavioral economics for decision support systems researchers

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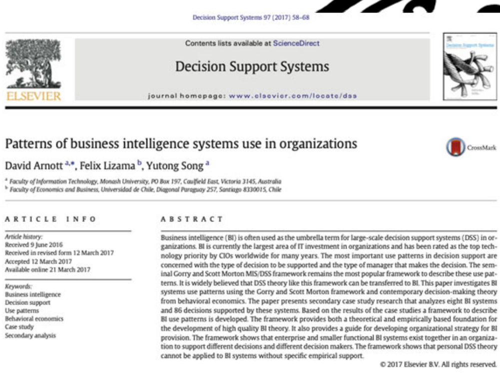
ARTICLE INFO

Keywords:
Behavioral economics
Decision-making
Dual process theory
Heuristics and biases
Decision support systems

ABSTRACT

Theories of decision-making, both prescriptive and descriptive, have long been important to decision support systems (DSS). Currently, the field of behavioral economics (BE) provides the dominant descriptive approach for understanding human decision-making. An indication of the field's standing is that three Nobel Prizes have been awarded to behavioral economics. Contemporary BE has two major theory foundations – the dual process theory of decision-making cognition and a set of judgment heuristics and cognitive biases. These foundations have been combined to create important theories like prospect theory and action strategies like nudging. Previous research has found that DSS has been slow to adopt recent advances in BE, even to the extent that some projects continue to use older theories like the phase model of decision making. This paper aims to make DSS researchers aware of contemporary BE, its nature, and its differences with early BE. We believe that behavioral economics is a useful and productive foundation for DSS research and that the use of BE in DSS should be significantly expanded.

Tools - Materiality



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Patterns of business intelligence systems use in organizations

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Secondary analysis

ABSTRACT

Business intelligence (BI) is often used as the umbrella term for large-scale decision support systems (DSS) in organizations. BI is currently the largest area of IT investment in organizations and has been rated as the top technology priority by CIOs worldwide for many years. The most important use patterns in decision support are concerned with the type of decision to be supported and the type of manager that makes the decision. The seminal Gorry and Scott Morton MIS/DSS framework remains the most popular framework to describe these use patterns. It is widely believed that DSS theory like this framework can be transferred to BI. This paper investigates BI systems use patterns using the Gorry and Scott Morton framework and contemporary decision-making theory from behavioral economics. The paper presents secondary case study research that analyzes eight BI systems and 86 decisions supported by these systems. Based on the results of the case studies a framework to describe BI use patterns is developed. The framework provides both a theoretical and empirically based foundation for the development of high quality BI theory. It also provides a guide for developing organizational strategy for BI provision. The framework shows that enterprise and smaller functional BI systems exist together in an organization to support different decisions and different decision makers. The framework shows that personal DSS theory cannot be applied to BI systems without specific empirical support.

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Materiality: Tools- history. Power et al (2019)

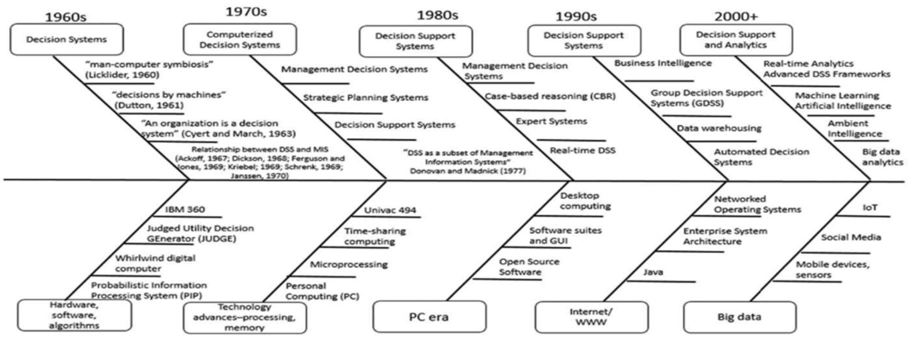

Figure 3. Advances in Decision Systems and Technology.

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ERP systems: AUTOMATE **Integration.** Transactional Data

EDI, **Internet EDI**, or **extranets** are used to connect a company's ERP system to the IT systems of its suppliers and customers.

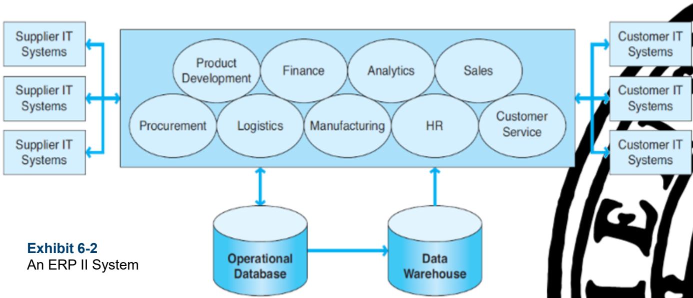

Exhibit 6-2
An ERP II System

SO 3 Current ERP system characteristics

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Materiality: Tools – history/Legacy. Functionality & Use ("Design & Use").

270 **A critical analysis of DSS revisited** D Arnott and G Pervan

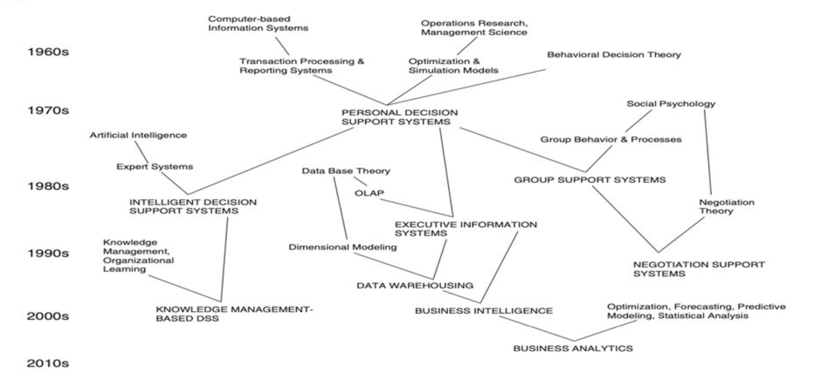

Figure 1 The genealogy of the DSS field, 1960–2010.

The AI – environment/ development? Royal Society: Turing Test vs Searle, "Chinese Room

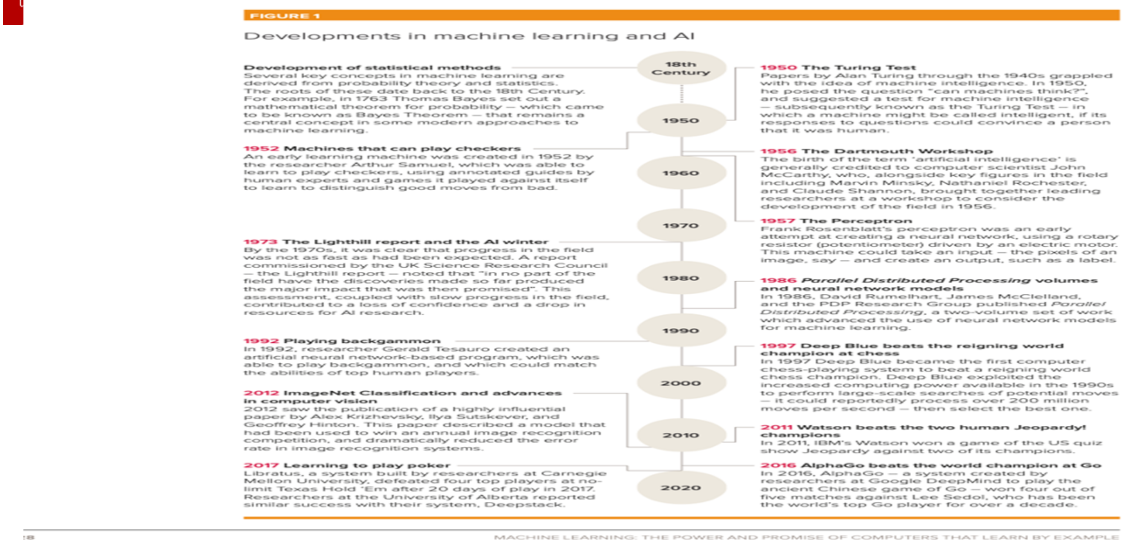

FIGURE 1

Developments in machine learning and AI

18th Century · 1950 · 1960 · 1970 · 1980 · 1990 · 2000 · 2010 · 2020

Development of statistical methods
Several key concepts in machine learning are derived from probability theory and statistics. The roots of these date back to the 18th Century. For example, in 1763 Thomas Bayes set out a mathematical theorem for probability — which came to be known as Bayes Theorem — that remains a central concept in some modern approaches to machine learning.

1952 Machines that can play checkers
An early learning machine was created in 1952 by the researcher Arthur Samuel, which was able to learn to play checkers, using annotated guides by human experts and games it played against itself to learn to distinguish good moves from bad.

1973 The Lighthill report and the AI winter
By the 1970s, it was clear that progress in the field was not as fast as had been expected. A report commissioned by the UK Science Research Council — the Lighthill report — noted that "in no part of the field have the discoveries made so far produced the major impact that was then promised". This assessment, coupled with slow progress in the field, contributed to a loss of confidence and a drop in resources for AI research.

1992 Playing backgammon
In 1992, researcher Gerald Tesauro created an artificial neural network-based program, which was able to play backgammon, and which could match the abilities of top human players.

2012 ImageNet Classification and advances in computer vision
2012 saw the publication of a highly influential paper by Alex Krizhevsky, Ilya Sutskever, and Geoffrey Hinton. This paper described a model that had been used to win an annual image recognition competition, and dramatically reduced the error rate in image recognition systems.

2017 Learning to play poker
Libratus, a system built by researchers at Carnegie Mellon University, defeated four top players at no-limit Texas Hold 'Em after 20 days of play in 2017. Researchers at the University of Alberta reported similar success with their system, Deepstack.

1950 The Turing Test
Papers by Alan Turing through the 1940s grappled with the idea of machine intelligence. In 1950, he posed the question "can machines think?", and suggested a test for machine intelligence — subsequently known as the Turing Test — in which a machine might be called intelligent, if its responses to questions could convince a person that it was human.

1956 The Dartmouth Workshop
The birth of the term 'artificial intelligence' is generally credited to computer scientist John McCarthy, who, alongside key figures in the field including Marvin Minsky, Nathaniel Rochester, and Claude Shannon, brought together leading researchers at a workshop to consider the development of the field in 1956.

1957 The Perceptron
Frank Rosenblatt's perceptron was an early attempt at creating a neural network, using a rotary resistor (potentiometer) driven by an electric motor. This machine could take an input — the pixels of an image, say — and create an output, such as a label.

1986 *Parallel Distributed Processing* volumes and neural network models
In 1986, David Rumelhart, James McClelland, and the PDP Research Group published *Parallel Distributed Processing*, a two-volume set of work which advanced the use of neural network models for machine learning.

1997 Deep Blue beats the reigning world champion at chess
In 1997 Deep Blue became the first computer chess-playing system to beat a reigning world chess champion. Deep Blue exploited the increased computing power available in the 1990s to perform large-scale searches of potential moves — it could reportedly process over 200 million moves per second — then select the best one.

2011 Watson beats the two human Jeopardy! champions
In 2011, IBM's Watson won a game of the US quiz show Jeopardy against two of its champions.

2016 AlphaGo beats the world champion at Go
In 2016, AlphaGo — a system created by researchers at Google DeepMind to play the ancient Chinese game of Go — won four out of five matches against Lee Sedol, who has been the world's top Go player for over a decade.

18 MACHINE LEARNING: THE POWER AND PROMISE OF COMPUTERS THAT LEARN BY EXAMPLE

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Statistics – The Language of Big Data! (Volume, Variety, Velocity).

”One good working definition of statstics might be that it is the technology of **extracting meaning** from data”. **Descriptive statistics**

”..the technology of handling **uncertainty**.” **Predictive Statistics**

Spiegelhalter, 2019, *The Art of Statistics*, p 7

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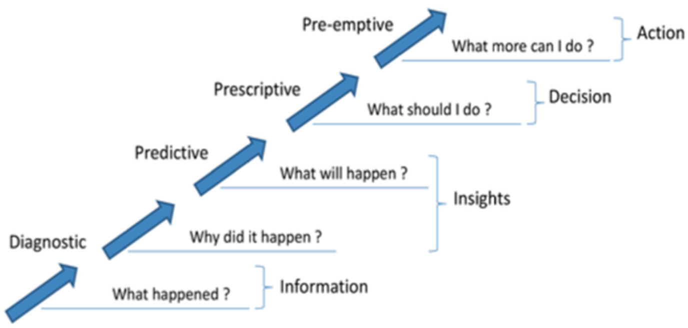
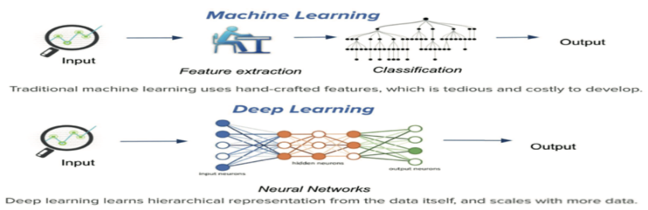
Expectations: Different views – descriptive (what happened?) and predictive (what **will** happen?)

Fig. 7 From hindsight to insight to foresight (based on HP 2014)



Springer

”Learning” Programming vs Statistics



Analytics – old (RDBM; Query) and new.

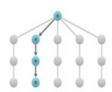
According to Qlik!

Qlik

Datasheet

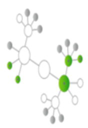
Relational Databases and Queries are Old Technology

Simply put, relational databases and SQL queries were not designed for modern analytics. While it's true that SQL is required to pull data from many sources, most analytics tools depend on SQL and query based approaches as their fundamental architecture for modeling data and supporting interactivity. This is a major flaw – resulting in restricted linear exploration and analysis on partial subsets of data. Data sources must be brought together using SQL joins, and assumptions must be made in advance about what types of questions users will have. All other data is left behind. If a user wants to pivot their analysis based on something they discover, they will likely have to re-build complex queries, which often means going back to more experienced data experts. We call this the “ask, wait, answer cycle”. Every new type of question has a waiting period.



x Partial subsets of data
x Restricted linear exploration
x Slow performance
x **“Ask, wait, answer” cycle**

The Qlik Associative Engine – Built for Modern Analytics



✓ All your data
✓ Explore without boundaries
✓ Speed of thought
✓ **Unexpected insights**

The Qlik Associative Engine is designed specifically for interactive, free-form exploration and analysis. It fully combines large numbers of data sources and indexes them to find the possible associations, without leaving any data behind. It offers powerful on-the-fly calculation and aggregation that instantly updates analytics and highlights associations in the data, exposing both related and unrelated values after each click. This means people are free to search, explore, and pivot based on what they see, without limitations and without having to go back to experts and wait. That is why Qlik users consistently discover previously unforeseen insights which have been missed by query based tools, driving tremendous value. That's The Associative Difference – and only Qlik can deliver it.

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Ideas about decision

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Ideas: Tradition vs Alternative (Behavioral Economics)

Bentham vs Kant

Tradition – von Neumann & Morgenstern

- (Expected) Utility theory
- One person, one point of time, one dimension. Perception & Preferences given.
- Rational Choice – ”Game Theory”, ”Prisoners Dilemma”.
- ”Desktop” – **prescriptive/normative, axioms**

”Alternative” Behavioral Economics & Others

- Prospect Theory
- ”Person & Situation”. ”Social history”.
- Behavioral Economics: System 1 & System 2.
- **Frames/framing: framing, naming, relating.**
- Experiments – Laboratory
- Klein – intuition, naturalistic decision making
- Gigerenzer – evolutionary approach

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Central Assumptions/Concepts in Decision Theory/Making and Organisational Design (e.g. Design Science; Nudging).

- Uncertainty (unclear causality/"relations") & Risk ("identified relations").
- Choice/s (Logic of consequences) vs. Judgement (Logic of Appropriateness).
- Causality (cause & effect) & Correlation.
- Linearity vs Non-Linearity (Exponential growth; Power Laws).

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Some aspects…

- Individual ("egoism") vs Social/Group ("Altruism"; "Wisdom of Crowds").
- Programmed vs Non-programmed decision (c.f. Strategic- Tactic- Operative).
- Facts (cognition) vs Values (emotions, "affects").
- Logic of Consequences ("efficiency"; calculation; means/ends) & Logic of Appropriateness (legitimacy; "fair").

Person & Situation ("SocialPsycology"): The Situation

Complexity leads to use of **uncertainty** leads to use of heuristics – can lead to cognitive mistakes.

- **Complexity**: difficult to identify causality (cause and effect). Interdependencies, non-linearity.
- **Uncertainty:** difficult to calulate risk.
- **Heurstics:** Rule of thumb
- **Cognitive mistakes/biases**: "Systematic". Often related to System 1 thinking.

The Logic of Appropriateness. Person & Situation (Rules, Norms, Values, "Culture")

Decision makers are imagined to ask (explicitly or implicitly) three questions:

1. The question of **recognition**. What kind of situation is this?
2. The question of **identity**: What kind of person am I? Or what kind of organization is this?
3. The **question of rules:** What does a person such as I, or an organization such as this, do in a situation such as this?

March, (1993, p 58) *A Primer on Decision Making. How Decisions Happen*.

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Puzzles vs. Mysteries

”A *puzzle* has well-defined rules and a single solution, and we know when we have reached the solution. Puzzles deliver the satsifaction of a **clear-cut task** and **a correct answer**.

”Mysteries offer *no such clarity of definition*, and no objectively correct solution; they are imbued with vagueness and indeterminacy. We approach mysteries by asking **’ What is going on here?,** and recognise that even afterwards **our understanding is likely to be only partial.** They provide none of the comfort and pleasure of reaching the ’right’ answer.”

Kay & King (2020) *”Decision- Making Beyond The Numbers”*

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Mystery. Cf. Wicked Problems

”A mystery cannot be solved as a crossword puzzle can; it can only be framed, by identifying the critical factors and applying some sense of how these factors have interacted in the past and might interact in the present or future”.

Kay & King (2020, p 20-21) *Radical Uncertainty. Decision- Making Beyond the Numbers*

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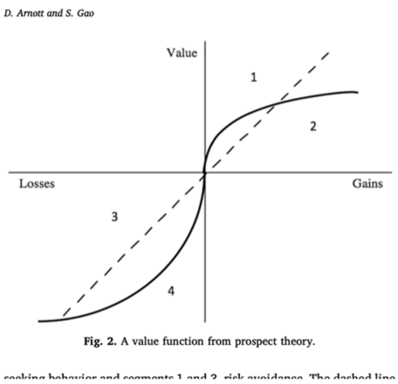
Different situations – different decisions, different actions!

Expected utility vs Prospect Theory



Changes from a baseline

”People think about life in terms of **changes, not levels**. They can be changes from the status quo or changes from what was expected, but whatever form they take it is changes that **make us happy or miserable**”

Thaler (2015, p.32) *Misbehaving*

Framing (and naming) is important!

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General heuristics/biases

- The availability heuristic: you use what you **remember**. The importance of memory.
- The representative heuristic: signals/traits that correspond with previously formed **stereotypes**
- The confirmation heuristic: search and collects data (use selective data) when testing ideas/hypotheses.
- The affect heuristic: follow a emotional evaluation before an analytic

Bazerman & Moore (2013, p 7) *Judgement in Managerial Decision Making*

Ex. 1 Emotional Framing - **the importance of wording**..

- Would you accept a gamble that offers a 10% chance to **win** $95 and a 90% chance to **lose** $5?
- Would you pay $5 to participate in a lottery that offers a 10% chance to win $100 and a 90% chance to win nothing?

…**losses** evokes stronger negative feelings than gains.

Khaneman (2011, p 364).

Ex 2. Chosing method

Background: Physician participants were given statistics about the outcomes of two treatements for lung cancer: surgery and radiation. The five – years survival rates clearly favour surgery, but in the short term surgery is riskier than radiation. The two descriptions of the short-term outcomes of surgery were:

- The one-month survival rate is 90%
- There is 10% mortality in the first month.

Surgery more popular in the first ”narrative”: 84 vs 5

Khaneman (2011, p 367).

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Explanation

”Humans are social animals and communication plays an important role in decision-making. **We frame our thinking in terms of narratives**. And able leaders – whether in business, in politics, or in everyday life – make decisions, both personal and collective, by talking with others and being open to challenge from them.”

Kay & King (2020, p.17) *Decision- Making Beyond The Numbers*

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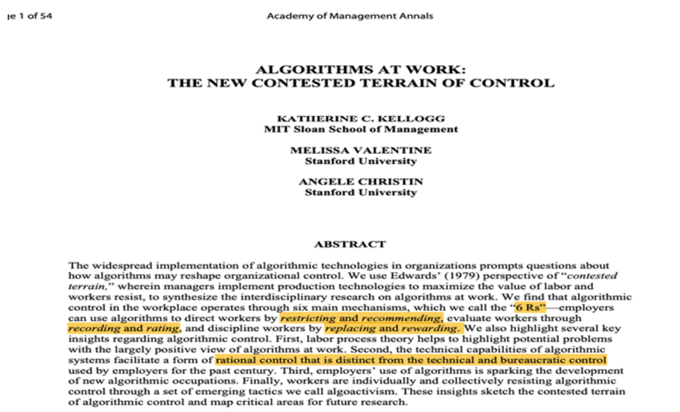
”Contested Terrain”: Maximation of Labor Value & Workers Resistance. Skilling & De-skilling. Conflict


ıe 1 of 54

Academy of Management Annals

ALGORITHMS AT WORK:
THE NEW CONTESTED TERRAIN OF CONTROL

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ABSTRACT

The widespread implementation of algorithmic technologies in organizations prompts questions about how algorithms may reshape organizational control. We use Edwards' (1979) perspective of "*contested terrain,*" wherein managers implement production technologies to maximize the value of labor and workers resist, to synthesize the interdisciplinary research on algorithms at work. We find that algorithmic control in the workplace operates through six main mechanisms, which we call the "6 Rs"—employers can use algorithms to direct workers by *restricting* and *recommending*, evaluate workers through *recording* and *rating*, and discipline workers by *replacing* and *rewarding*. We also highlight several key insights regarding algorithmic control. First, labor process theory helps to highlight potential problems with the largely positive view of algorithms at work. Second, the technical capabilities of algorithmic systems facilitate a form of rational control that is distinct from the technical and bureaucratic control used by employers for the past century. Third, employers' use of algorithms is sparking the development of new algorithmic occupations. Finally, workers are individually and collectively resisting algorithmic control through a set of emerging tactics we call algoactivism. These insights sketch the contested terrain of algorithmic control and map critical areas for future research.

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What can algorithms do? Algorithms & **affordance**

Table 1: New Technological Affordances of Algorithms

Affordances of Algorithmic Systems	Key Insights	Example Studies
Comprehensive	• Wide range of devices and sensors • Collecting a variety of data about workers, from biometrics to accelerometers, text messages, and online footprints	Ball & Margulis (2011); Xu et al. (2014); Beane & Orlikowski (2015); Levy (2015); Angrave et al. (2016); Goldberg et al. (2016); Harari, Müller, Aung, & Renfrow (2017); Leonardi & Contractor (2018); Lix, Goldberg, Srivastava, & Valentine (2019); Landay (2019)
Instantaneous	• High velocity of algorithmic computation • Performance assessments incorporated in real-time into the system	Jacobs (2009); Katal et al. (2013); Etter, Kafsi, Kazemi, Grossglauser, & Thiran (2013); Mayer-Schönberger & Cukier, (2013); Sachon & Boquet (2017); Crowston & Bolici, (2019)
Interactive	• Algorithmically-mediated platforms allow for participation from multiple parties • Interactive interfaces channel user behavior in real-time	Chalmers & MacColl, (2003); Holzinger & Jurisica (2014); Amershi et al. (2014); Kulesza et al. (2015); Cambo & Gergle (2018); Valentine et al. (2017); Zhou, et al. (2018)
Opaque	• Intellectual property and corporate secrecy • Technical literacy • Machine-learning opacity	Pasquale (2010); Orlikowski & Scott (2014b); Bolin & Andersson Schwarz (2015); Dietvorst et al. (2015); Diakopoulus (2015); Burrell (2016); Danaher (2016); Weld & Bansal (2018)

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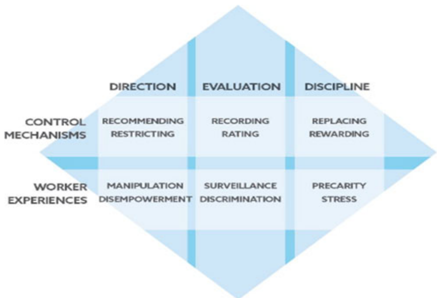
Result – how do employees experience use of algorithms?

Figure 1. Review of Algorithmic Control as Contested Terrain



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DIRECTING: Recommending & Restricting

Table 2: Algorithmic Direction

	Algorithmic Direction	Key Insights	Example Studies
Algorithmic Recommending	Prompting the worker to make decisions preferred by the choice architect Recommending specific courses of action	Can augment workers' decisions by automatically finding patterns in the data and prescribing actions based on this Can bypass the heuristics workers typically use to make decisions	Gabrilovich et al. (2004); Goldman et al. (2011); Pachidi et al. (2014); Danaher (2016); Rosenblat & Stark (2016); Schreiber (2017); Gupta (2018); Veale et al. (2018); Karunakaran (2019); Valentine (2019)
Algorithmic Restricting	Restricting access to information Restricting behavior	Can continuously and covertly restrict information available to workers Can interactively restrict the behavior of crowdworkers and online community members	O'Mahony & Bechky (2008); West & O'Mahony (2008); Muthukumaraswamy (2010); Shaikh & Cornford, (2010); Faraj, Jarvenpaa, and Majchrzak (2011); Afuah & Tucci (2012); Treem and Leonardi (2012); Majchrzak et al. (2013); Aneesh et al. (2014); Kallinikos & Tempini (2014); Orlikowski & Scott (2014a); Orlikowski & Scott, (2014b); Lee et al. (2015); Tempini (2015); Arazy et al. (2016); Barrett et al. (2016); Fayard, Gkeredakis, & Levina (2016); Lakhani (2016); Leonardi and Vaast (2016); Calo & Rosenblat (2017); Lifshitz-Assaf (2018); Kittur et al. (2019); Truelove (2019)
Potential Worker Experiences	Frustration Bias Overriding workers' conceptions of well-being Reduced voice Precarity	Recommendations may not be intelligible to workers, resulting in frustration Recommendations can reinforce social and racial inequalities Recommendations may negatively affect the welfare of those being nudged Restrictions can prevent workers from communicating with managers and with one another Restrictions can break jobs down into "micro" tasks, which can be scheduled in finely-grained, opaque, and unpredictable ways	Angwin et al. (2007); Martin et al. (2014); Pachidi et al. (2014); Askay (2015); Lee et al. (2015); Salehi et al. (2015); Barocas & Selbst (2016); Danaher (2016); O'Neil (2016); Rosenblat & Stark (2015); Brayne (2017); Christin (2017); Yeung (2017); Vallas (2018); Gray & Suri (2019); Vallas & Schor (2020)

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EVALUATING: Recording & Rating

Table 3: Algorithmic Evaluation

	Algorithmic Evaluation	Key Insights	Example Studies
Algorithmic Recording	Recording and aggregate finely-grained behavior and statistics from internal and external sources Providing real-time feedback	Can track a wide range of behaviors Can enable real-time adjustments of worker performance	Alvesson & Karreman (2007); Watkins, Allen, Coopman, Hart, & Walker (2007); McClelland (2012); Segal et al. (2014); Karunakaran (2016); Levy (2016); Rosenblat & Stark (2016); Leonardi & Contractor (2018); Schweyer (2018); Bailey, Erickson, Silbey, & Teasley (2019); Kittur et al. (2019); Lehdonvirta et al. (2019); Lix et al. (2019); Rahman (2019)
Algorithmic Rating	Using online rating and ranking Using predictive analytics	Can aggregate quantitative and qualitative data to measure work productivity and to evaluate workers within an organization based on external and internal sources Can predict future worker performance- achievement, skillset, potential, retention, etc	Orlikowski & Scott (2014b); Varshney et al. (2014); Ramamurthy et al. (2015); Barrett, Oborn, & Orlikowski (2016); Horesh et al. (2016); King (2016); Mallafi & Widyantoro (2016); Christin (2018); Jharver et al. (2018); Levy & Barocas (2018); Rosenblat (2018); Curchod et al. (2019); Rahman (2019); Lix & Valentine (2019)
Potential Worker Experiences	Loss of privacy Data accuracy Discrimination Weight of ratings in hiring decisions	Workers may be concerned that the data collected may include their overall aptitude in various skills in work and home settings, and their physical and mental health Workers may not be aware of the data being collected, so they may not be able to appeal judgements against them or correct misinformation. Algorithmic recording and ratings can be subject to gender and race stereotyping; workers may have fewer mechanisms for contesting mechanisms they feel are unfair; consumer rating may escape legal action Workers may be concerned that employers may select workers primarily based on prior ratings and may communicate with workers primarily via online tools that do not allow in-person assessments of workers	Angwin (2014); Tufekci (2014); Bock (2015); Miller (2015); O'Connor (2015); Ahmed et al. (2016); Fourcade & Healy (2016); Rosenblat & Stark (2016); Bodie, Cherry, McCormick, & Tang (2017); Greenwood, Adjerid, & Angst (2017); Levy & Barocas (2017); Rosenblat, Levy, Barocas, & Hwang (2017); Rahman & Valentine (2017); Anteby & Chan (2018); Chan & Wang (2018); Jhaver, Karpfen, & Antin (2018); Lix &Valentine (2019); Ticona & Mateescu (2018); Rahman (2019); Valentine & Bernstein (2019); Wood et al. (2019); Wood and Lehdonvirta (2019)

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DISCIPLINE: Replacing & Rewarding

Table 4: Algorithmic Discipline

	Algorithmic Discipline	Key Insights	Example Studies
Algorithmic Replacing	Automatically replacing or removing Immediately replacing or removing	Can be used to fire underperforming workers and replace them with others that will follow managerial directives Can recruit on a greater scale and at the fraction of the time because people are interchangeable and labor is mainly digital	Aneesh (2009); Kittur, Smus, Khamkar, & Kraut (2011); Lenglet (2011); Kittur et al. (2013); Retelny et al. (2014); Beunza & Millo (2015); De Stefano (2015); Irani (2015); Lee et al. (2015); Borch & Lange (2016); Ha-Thuc et al. (2016); Lange, Lenglet, & Seyfert (2016); Lenglet & Mol (2016); Rosenblat &Stark (2016); Sundararajan (2016); Valentine et al. (2017); Rahman (2019); Ajunwa & Greene (2018); Cherry & Aloisi (2018); MacKenzie (2018); Shapiro (2018); Jackson (2019); Jarrahi et al. (2019)
Algorithmic Rewarding	Interactively and dynamically rewarding Gamifying rewards	Can provide rewards in real time for behaviors that comply with predefined correct behaviors Can use the principles of game design to make the affective experience of work more positive and "fun" for employees	Edery & Mollick (2009); Deterding, Khaled, Nacke, & Dixon (2011); Kerfoot & Kissane (2014); Mollick & Rothbard (2014); Walz & Deterding (2014); Bogost (2015); Irani (2015); Rosenblat & Stark (2016); Stanculescu, Bozzon, Sips, & Houben (2016); Rahman (2017); Ivanova et al. (2018); Kim (2018); Lehdonvirta (2018); Liu, Huang, & Zhang (2018); Petre (2018); Shapiro (2018);
Potential Worker Experiences	Precarity Frustration and stress	Precarity can be greater for low-skilled workers, especially if they work for organizations that use platforms that allow for automatic replacement Intentional secrecy of rewarding system and rapid responsiveness of the rewards may lead to worker frustration and stress	Kleemann, Voß, & Rieder (2008); Aneesh (2009); Kittur et al. (2011); Schenk & Guittard (2011); Irani & McClelland (2012); Silberman (2013); Bergvall-Kåreborn & Howcroft (2014); Martin et al. (2014); Retelny et al. (2014); Dourish (2016); Gray, Suri, Ali, & Kulkarni (2016); Postigo (2016); Raval & Dourish (2016); Barley et al. (2017); Corporaal & Lehdonvirta (2017); Graham, Hjorth, & Lehdonvirta (2017); Valentine et al. (2017); Schwartz (2018); Rahman (2019)

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Knowledge Worker

A need of managing a new resource – knowledge!

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Research article

Managing knowledge and managing knowledge work: what we know and what the future holds

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Abstract
In this paper we review the recent IS literature on knowledge and consider different assumptions that underpin different approaches to this broad research area. In doing this we contrast those who focus on knowledge management with those who focus on knowing as practice and examine how contexts, processes and purposes need to be considered whichever approach to knowledge one is adopting. We also identify how recent IT developments, especially in relation to social software and the digitization of everything, are presenting new opportunities (and challenges) for how organizations can manage both knowledge and knowledge work. This presents IS scholars with new research agendas for examining and understanding the relationships between technology, organization and society.
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Keywords: knowledge management; knowledge work; knowledge management systems; social software; digitization

Different Approaches to KM

Table 1 Comparison of different approaches to managing knowledge

Approaches to managing knowledge	*Repository*	*Network*	*Crowd*	*Sensor*
IT support	Databases and search engines	Peer-to-peer virtual networks	Platforms that enable as many voices as possible to contribute	Tracking devices in technologies
Outcomes	Reuse of explicit knowledge for efficiency	Sharing of tacit knowledge for improved innovation within organization	Wisdom of crowd to support fast open innovation	Datification that can reveal patterns that can be used for decision-making, regardless of understanding why
Issues	Creating culture of trust; incentives for sharing; quality of knowledge	Pragmatic boundaries; power asymmetries	Protection of firm IP; rewarding participants who are not employees; novelty of ideas	Political, economic, social and legal issues