Executive Master in Finance & Control program
Experience Session 31 October 2023

Today’s topic: Data Analytics & Business Intelligence

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VRIJE UNIVERSITEIT AMSTERDAM
School of Business and Economics
EXECUTIVE EDUCATION

Contents

1. Introduction

Personal introduction Bert Steens

Education

Econometrics (MSc, EUR); postgraduate controllers program (RC, VU); post academic change management program (Master in change management, SIOO); dissertation (PhD/Dr, VU) “Impacts of Transfer Pricing on Value Creation”

Positions

1987 – 1989: AkzoNobel (Akzo Systems), consultant Financial Information systems
1989 – 1999: EY, consultant – senior consultant – executive consultant
1999 – 2000: EY, partner
2000 – 2018: VU Amsterdam, part time university professor VU Amsterdam
2000 – 2005: Cap Gemini Ernst & Young, vice president, service line leader
2005 – 2018: EY, partner, service line leader
2018 – Now: VU Amsterdam, full professor and program director

Academic

- Teaching post experience master students and executives
- Current research areas: Digitization and Datafication Finance Function; Sustainable Business Management; Transfer Pricing

Practice

- Experience: over 35 years relevant experience in the areas of business analytics, management control and accounting, transfer pricing, business controlling
- Roles: senior expert, member steering committees and quality assurance teams, advisor to senior executives

Be properly prepared for the future with the Controller programme at VU Amsterdam

Introduction to EMFC programme: 'all-round leader in finance aspiring to the CFO job'

All-round:

- Has ultimate responsibility for the provision of reliable internal and external information by organisations
- Takes responsibility for the economic rationality of the decisions taken within the organisation
- Proactively supports the development, execution and implementation of operational and strategic plans

They contribute to long-term value creation in complex organisations:

- Characterised by a focus on ever more digitalised 'end-to-end' primary and supporting business processes (outsourced or in-house)
- Where increasing importance is attached to internal and external data in the support of evidence based decision-making
- Where issues are multidisciplinary by definition

*: Study on the all-round controller: Steens, B., De Bont, A., Roozen, F. (2020). Influence of governance regime oncontroller roles – supervisory board members' perspectives on business unit controller roles and role conflict. Corporate Governance, 20(6), 1029-1051, https://doi.org/10.1108/CG-10-2019-0309.

Key characteristics (1/2)

1. The VU Amsterdam EMFC programme is the **first EMFC/RC-programme** and is acknowledged to be trend-setting. Over the coming years, the issues of **long-term value creation**, **end-to-end data-to-intelligence processes** and **personal leadership** will be key.

2. The programme is geared towards **complex organisations** in both the profit and non-profit segments. Professionals who are capable of meeting challenges in these types of organisations can find work anywhere.

3. The programme trains the student to be a '**Leader in Finance aspiring to the CFO job**'. To this end, the VU Amsterdam EMFC programme provides an excellent command of the key skills required for the 'backbone of finance', whilst also significantly contributing to the competencies needed to address the three issues identified above in practice.

4. The aspect of personal leadership is taught in such way that the students get to know themselves better and are able to have **more impact** in organisations as a result.

*: Study on the all-round controller: Steens, B., De Bont, A., Roozen, F. (2020). Influence of governance regime oncontroller roles – supervisory board members' perspectives on business unit controller roles and role conflict. Corporate Governance, 20(6), 1029-1051, https://doi.org/10.1108/CG-10-2019-0309.

Key characteristics (2/2)

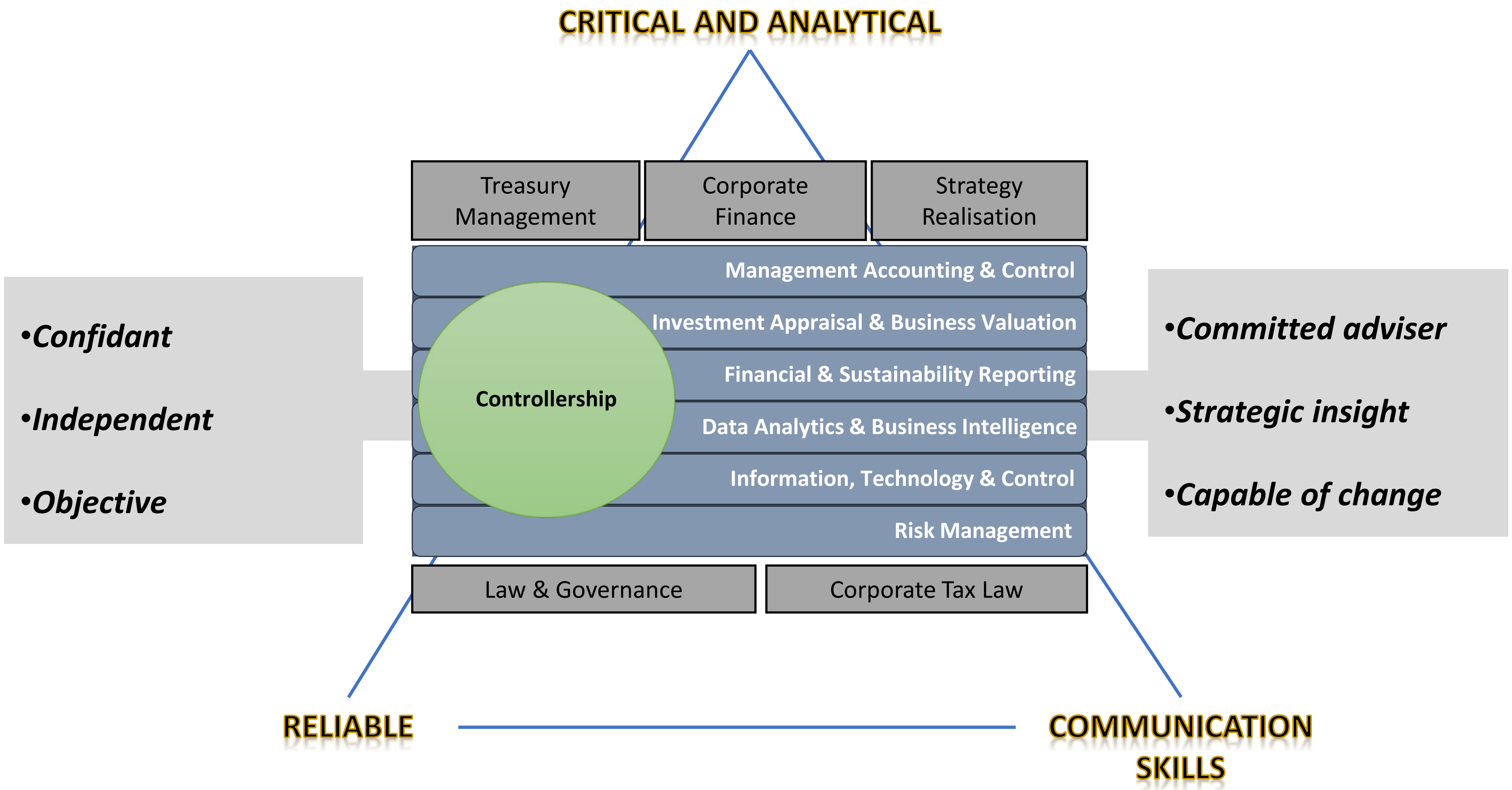
5. **From day one of the programme, the employer also benefits** from students' participation in the programme because they work in teams to resolve current issues from their own practice. The message to students is therefore 'From day one, you will be helping your own organisation, whilst also getting to know your own organisation better'.

6. The way in which students **graduate from the VU Amsterdam EMFC programme** is unique. They do so with a business project that solves a concrete issue from practice in a practical and scientific manner. Throughout the lecture programme, the students receive active supervision on a weekly basis.

7. The EMFC programme offers students the services of a **confidential counsellor** for advice on diverse matters. After all, there are many demands on young professionals, and combining the challenges of work, private life and studies is not always easy.

*: Study on the all-round controller: Steens, B., De Bont, A., Roozen, F. (2020). Influence of governance regime oncontroller roles – supervisory board members' perspectives on business unit controller roles and role conflict. Corporate Governance, 20(6), 1029-1051, https://doi.org/10.1108/CG-10-2019-0309.

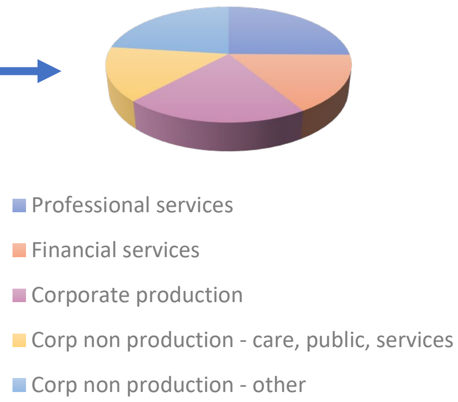
The all-round leader in finance has the hard and soft skills needed to act as a trusted adviser to management



Admissions characteristics

- Seniority:
  - A minimum of 2 years' work experience (requirement by VRC and VU EMFC)
  - Age: 26 – 35; plus several more experienced participants (even a few CFOs)
- Educational background:
  - Majority: MSc Accounting & Control, also business administrators and econometricians
  - VRC: maximum 10% 'HBO+'; in practice so far: 0 – 1 per cohort
- Employers and male/female:

Industry segment	2021 cohort	2020 cohort	2019 cohort	Average	
Professional services	23.7%	29.5%	22.4%	12	25.0%
Financial services	15.8%	20.5%	12.1%	7	15.7%
Corporate production	26.3%	11.4%	24.1%	10	20.7%
Corporate non-production - care, public, services	13.2%	18.2%	13.8%	7	15.0%
Corporate non-production - other	21.1%	20.5%	27.6%	11	23.6%
Total	100.0%	100.0%	100.0%	47	100.0%
Percentage males/females	73.7%/26.3%	72.7%/27.3%	73.7%/26.3%		73.4%/26.6%
# Self-employed				2-3	



- Resident in: Amsterdam area, Randstad
- Criteria for choosing VU Amsterdam: focus on analytics and IT, contemporary structure of AIS (integration of IT and IC to create I,T&C), location, recommendation from boss/colleagues
- Criteria for choosing other EMFC programmes: location, deficiencies, focus on soft skills/personal leadership

Current curriculum (62 ECTS) is geared towards a study duration of two years

Year 1

Sem. 1

R&C, F&C and S&C fundamentals:

- Controllership
- Management Control
- Financial & Sustainability Reporting
- Law & Governance

Integration paper

Sem. 2

Reporting & Control cluster, ctd.:

- Data Analytics & BI
- Management Accounting
- Risk Management
- Information, Technology & Control (comb. IT, IM, AIS & IC)

Integration practical

Integration paper

Year 2

Sem. 1

Finance & Control cluster:

- Investment Appraisal & Business Valuation
- Corporate Finance
- Corporate Tax Law
- Treasury Management

Valuation Paper

Sem. 2

Strategy & Control cluster:

- Strategic management perspective (Strategy)
- Management control perspective (AMC)

Strategic Initiative (SI) paper

Business Project

IT: Information Technology; **IM**: Information Management; **AIS**: Accounting Information Systems; **IC**: Internal Control; **AMC**: Advanced Management Control
(X): X ECTS per course; 1 ECTS ≈ 28 hours study load

Team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L&G


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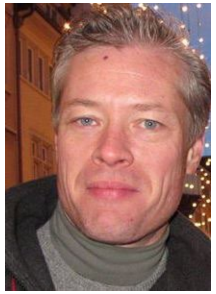
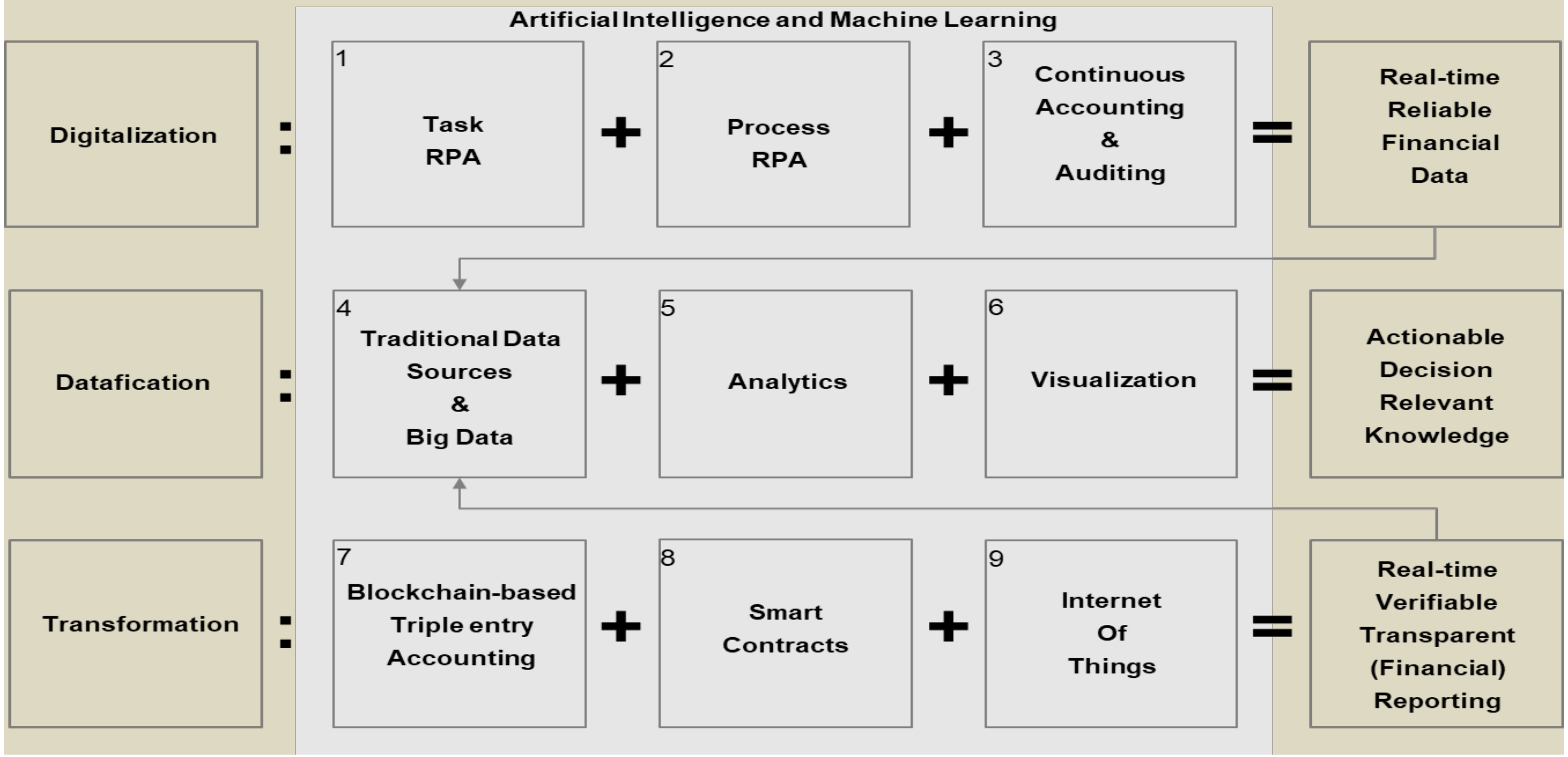
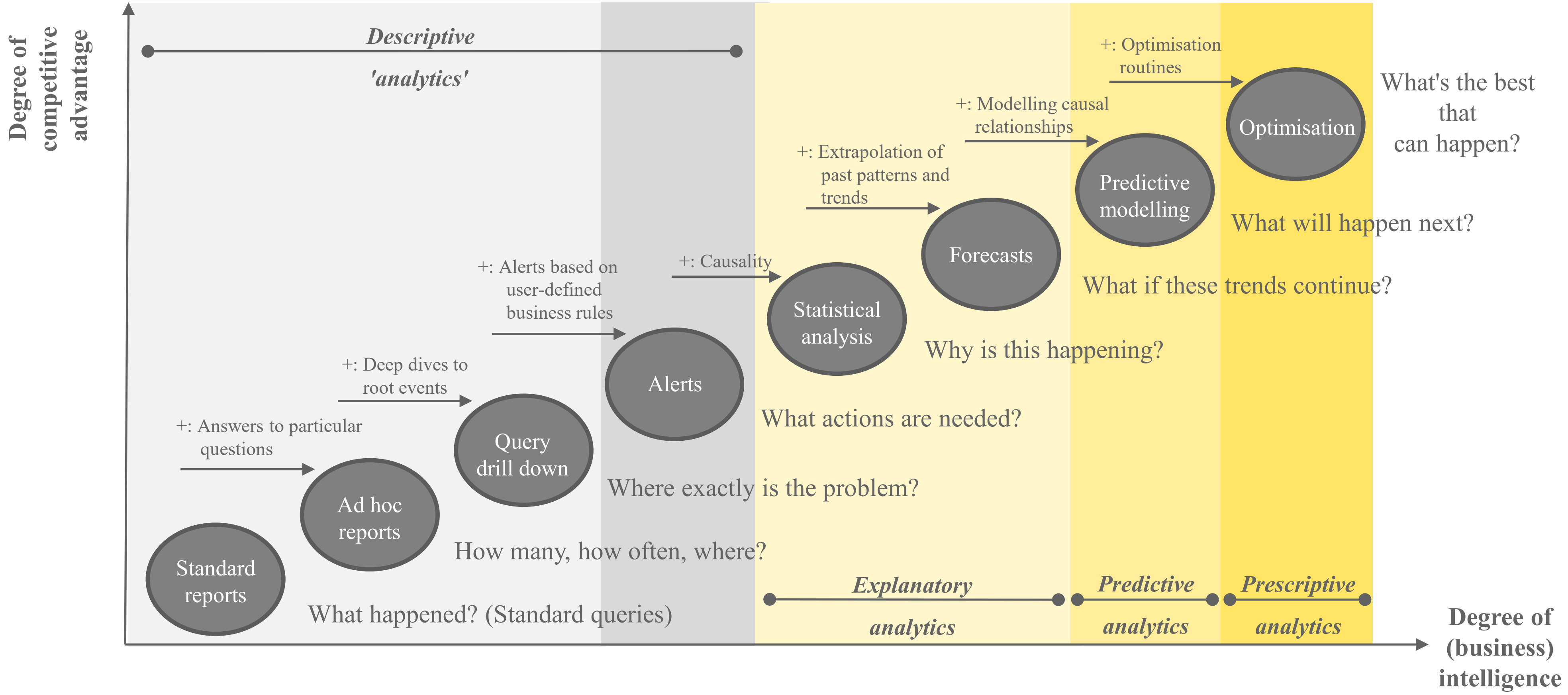

Ewald Liebegut
PO

Aspects of digitalisation, datafication and digital transformation are embedded in the current programme



Source: Roozen, F., B. Steens & L. Spoor. 2019. Technology: Transforming the Finance Function and the Competencies Management Accountants Need. *Management Accounting Quarterly*. 21(1): 1-14.

Example 1: Data Analytics & Business Analytics in Mgt Accounting



- Course taught on the basis of management accounting cases derived from practice
- Data Analytics & Business Intelligence: also relevant for other courses

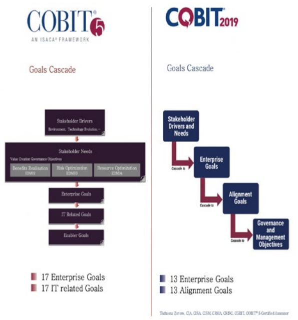
Sources: (1) Davenport, T.H. & J.G. Harris. 2017. Competing on Analytics – The new science of winning. Harvard Business Review Press. (2) Hardoon, D.R. & G. Shmueli. 2013. Getting Started With Business Analytics – Insightful Decision-Making. CRC Press.

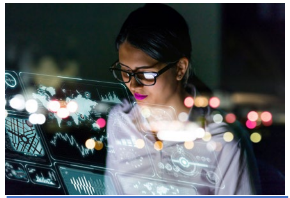
Example 2: Information, Technology & Control

Perspective on quality assurance data, quality frameworks (Data Governance Contingency Model, COBIT model) for the following areas:
- organisation, development
- change management
- data security & continuity management

Guest lecture: Organisational data governance and management, positioning of the IT function and the role of the CIO

Group discussion of practical case 1





Trends in IT and their impact on quality assurance

Guest lecture: Trends in IT

Group discussion of practical case 2

Quality assurance investment in IT (assuring delivery of development and change management objectives)

Guest lecture: Investment, change management and the role of the Finance function

Group discussion of practical case 3

External analysis (including hacking, GDPR, etc.)

Guest lecture: External threats including Hacking

Group discussion of practical case 4

Internal analysis (including misuse of data, fraud, etc.)

Guest lecture: Prevention, detection and response to internal threats including fraud

Group discussion of practical case 5

Monitoring and auditing (including digital auditing)

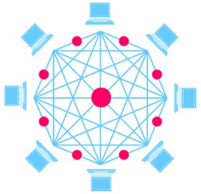
Guest lecture: Digital auditing and the controller

Group discussion of practical case 6

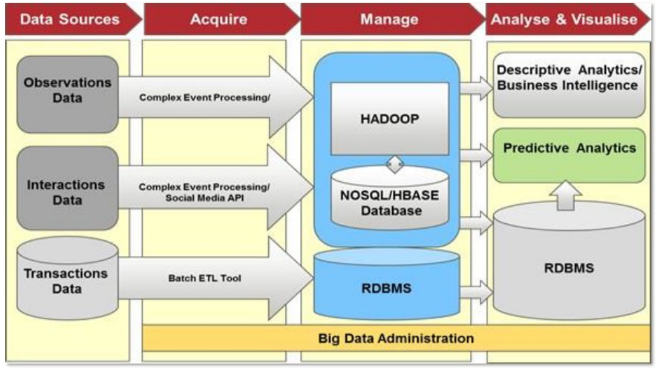
Blockchain and other developments

Guest lecture: Influence of developments in perspective on quality assurance

Group discussion of practical case 7



Information as a source and product of 'end-to-end' business processes, **Technology** as the supplier, transporter and processor of data (the raw material for information) and **Control** as the guarantor of reliability and quality of the information provided, examined in an integrated manner within the student's own business practice



Voice of students and former students

- Excellent evaluations (both course evaluations and exit evaluations)
- Ratings in Keuzegids Masters 2021 and 2022 higher education guides based on scores given by students: maximum score '++' for all five aspects (content, lecturers, assessment, career preparation, atmosphere)
- National Student Survey spring 2023 (2022): overall score 4.7 (4.4) on a scale of 1 to 5
- Alumni: there are over 1,750 graduate RCs who trained at VU Amsterdam; nearly 50 graduates per year on average over the course 36 years; Alumni Association brings together active and enthusiastic graduates (by means of networking events, lectures by CFOs, etc.)
- Survey among alumni in autumn 2021: evaluations of the individual courses generally good, ratings for the overall course (on graduation) ranging between 8 and 9
- Feedback from VU survey among alumni autumn 2021 (153 respondents, 12%):
  - Programme makes a positive contribution to professional competencies: 4.6 on a scale of 1 to 5
  - How likely are you to recommend the RC programme at VU Amsterdam (scale 1 – 10): 8.9

VU

Impression of kick-off seminar

Impression video 1 (available via website)

Introduction to the theme of today's Experience Session

Capabilities organizational level:

- Consistent set of strategies
- Data, IS and (big) data management
- AI & DA tooling
- Data scientists
- Leadership support, believe and budget

Evaluate performance current businesses and recommend improvements

Evaluate new business propositions and contribute to NBD

Contribute to Business Intelligence and Value Creation (F and ESG)

Capabilities individual level:

- Knowledge
- Cognitive competencies and ethical stewardship
- Managerial competencies
- Social interactive competencies
- Motivation and volition

2. Framework for Data Analytics & Business Intelligence

Data analytics & business intelligence Framework is based on key starting points (1/2)

Key starting points (hereafter: "KSP")

1. Data analytics comprise descriptive, explanatory, predictive and prescriptive analytics; Davenport & Harris (2017)* add autonomous analytics (referring to machine learning)
2. Data analytics are required to transform data into business intelligence, that literally refers to intelligence about the business of the company and its performance
3. This intelligence is required to become and stay competitive and to gain competitive advantage, even more so because of Big Data
4. The maturity of the application of analytics reflects the degree of (business) intelligence and – as a consequence – the degree of analytical competitiveness
5. Analytical techniques enabling the analysis of data and transformation of data into intelligence are selected based on the required insights and characteristics of the data

* Full reference of publication: Davenport, T.H., Harris, J.G., 2017, Competing on Analytics – the new science of winning, Harvard Business Review Press, Boston (ISBN 9781633693722)

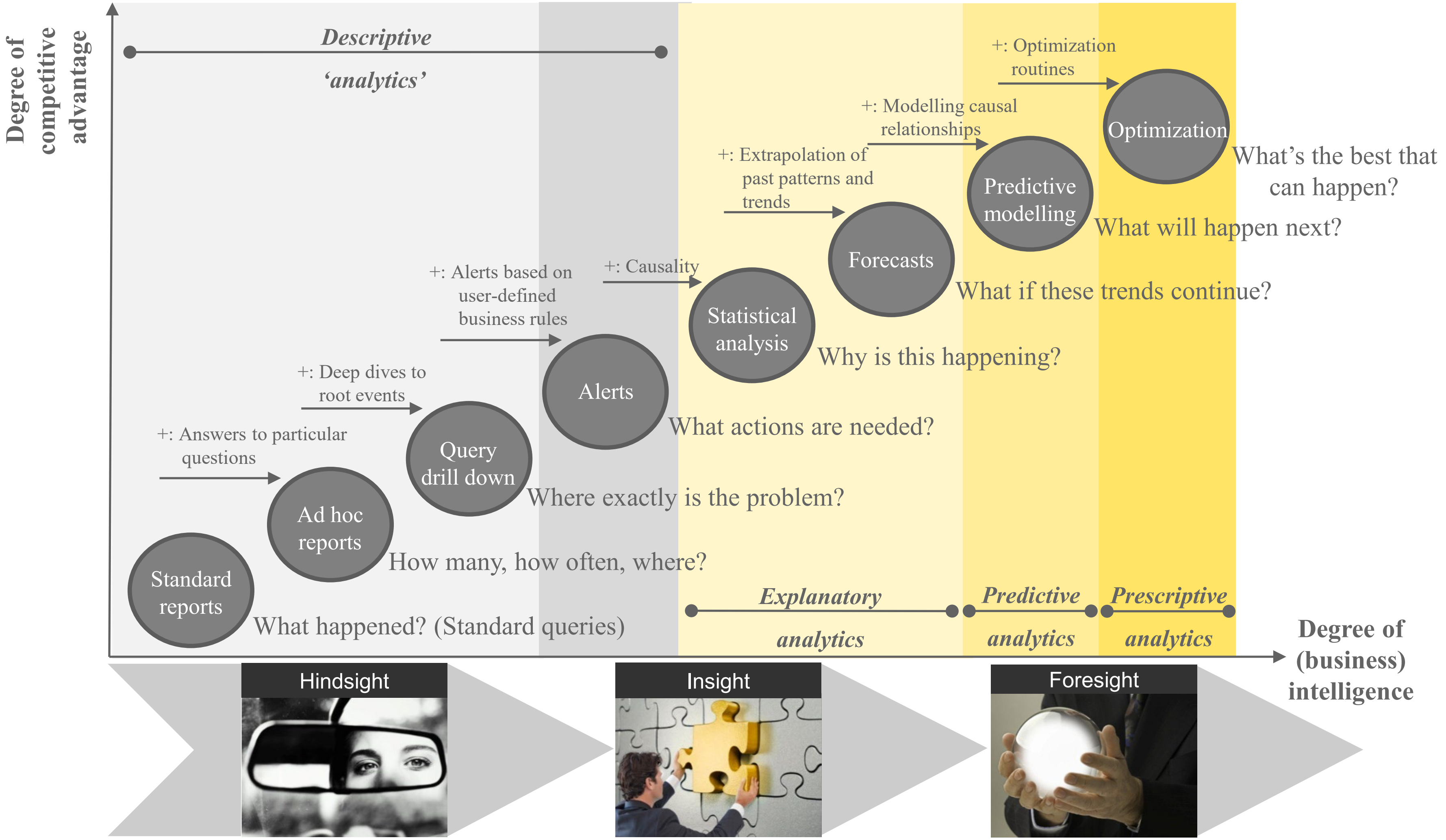
Data analytics & business intelligence Framework is based on key starting points (2/2)

Key starting points (hereafter: “KSP”) (ctd.)

6. The MADA framework structures the analytical techniques relevant for management accounting (‘managerial accounting’); these techniques largely originate from econometrics/operations research, statistics, mathematics, and IT
7. Analytical capabilities, data management capabilities, business acumen, organizational conditions and ethical stewardship are required to leverage from the potential of data and enable analytical techniques in a relevant and responsible way
8. As the impacts of digitalization, datafication and (digital) transformation on the work of controllers is substantial and still increasing, controllers aspire to develop their (digital) competencies, including data analytics competencies
9. In order to contribute to analytical competitiveness, controllers seek to apply these digital competencies together with their finance and control competencies and a clear understanding of the business, required organizational conditions and ethical challenges

Maturity of the application of analytics determines the degree of (business) intelligence and the degree of competitiveness

KSP 1 - 4

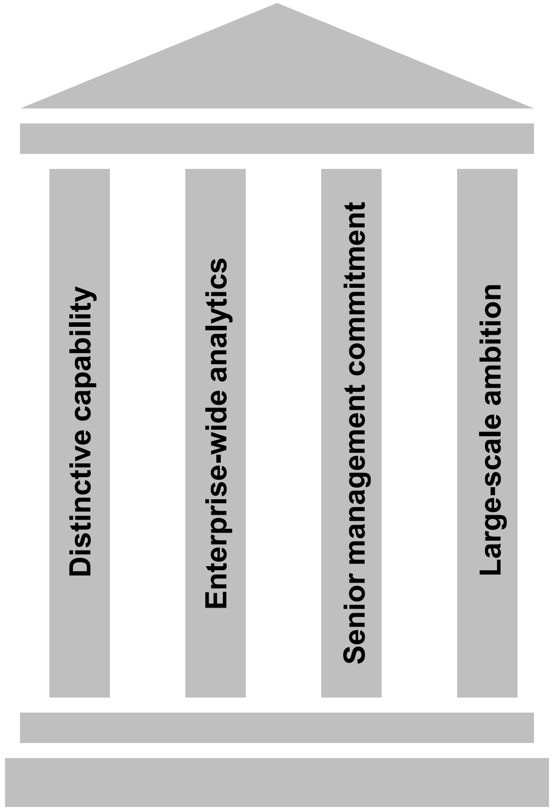


Sources: (a/o) Hardoon & Shmueli (2013, p. 13), Davenport & Harris (2017, p. 27)

Pillars and stages of analytical competition*

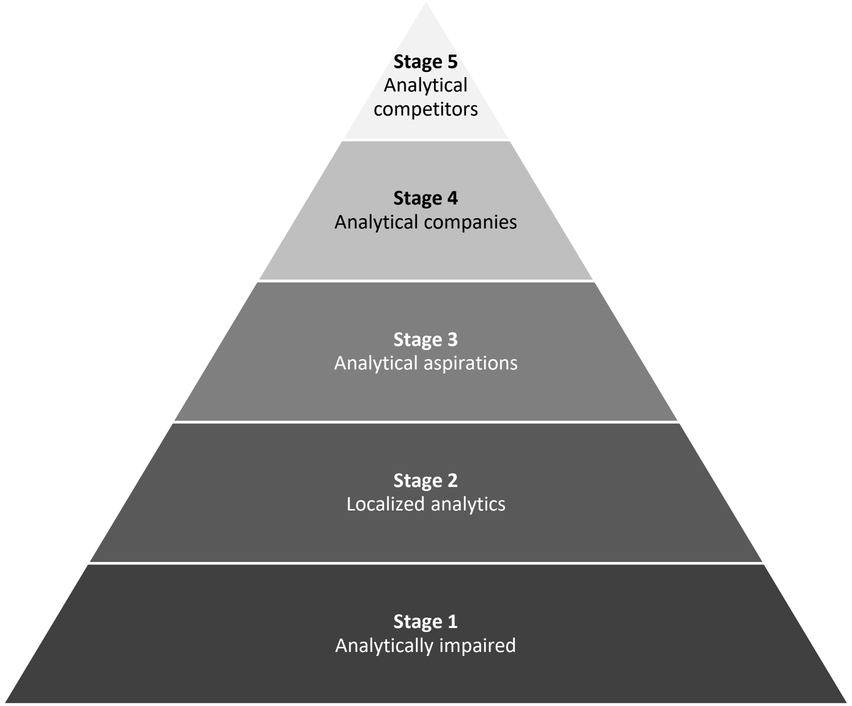
KSP 1 - 4

Four pillars of analytical competition refer to conditions/requirements



Five stages of analytical competition refer to the development process or the maturity stages

(see Davenport & Harris (2017, p. 62/Table 1) for distinctive capabilities and levels of insight per stage)



* See Davenport & Harris (2017, pp. 51 - 67)

TABLE 6-3

The DELTA model of analytical capabilities by stage

	Stage 1: Analytically impaired	Stage 2: Localized analytics	Stage 3: Analytical aspirations	Stage 4: Analytical companies	Stage 5: Analytical competitors
Data	Inconsistent, poor-quality, and unstandardized data; difficult to do substantial analysis; no groups with strong data orientation	Standardized and structured data, mostly in functional or process silos; senior executives do not discuss data management	Key data domains identified and central data repositories created	Integrated, accurate, common data in central repositories; data still mainly an IT matter, little unique data	Relentless search for new data and metrics leveraging structured and unstructured data (e.g., text, video); data viewed as a strategic asset
Enterprise	No enterprise perspective on data or analytics; poorly integrated systems	Islands of data, technology, and expertise deliver local value	Process or business unit focus for analytics; infrastructure for analytics beginning to coalesce	Key data, technology, and analysts managed from an enterprise perspective	Key analytical resources focused on enterprise priorities and differentiation
Leadership	Little awareness of or interest in analytics	Local leaders emerge but have little connection	Senior leaders recognize importance of analytics and developing analytical capabilities	Senior leaders develop analytical plans and build analytical capabilities	Strong leaders behave analytically and show passion for analytical competition
Targets	No targeting of opportunities	Multiple disconnected targets, typically not of strategic importance	Analytical efforts coalesce behind a small set of important targets	Analytics centered on a few key business domains with explicit and ambitious outcomes	Analytics integral to the company's distinctive capability and strategy
Analysts	Few skills that are attached to specific functions	Unconnected pockets of analysts; unmanaged mix of skills	Analysts recognized as key talent and focused on important business areas	Highly capable analysts explicitly recruited, developed, deployed, and engaged	World-class professional analysts; cultivation of analytical amateurs across the enterprise

TABLE 6-4

Additional technical capabilities for advanced analytics

	Stage 1: Analytically impaired	Stage 2: Localized analytics	Stage 3: Analytical aspirations	Stage 4: Analytical companies	Stage 5: Analytical competitors
Technology	Desktop technology, standard office packages, poorly integrated systems	Individual analytical initiatives, statistical packages, descriptive analytics, database querying, tabulations	Enterprise analytical plan, tool and platforms; predictive analytical packages	Enterprise analytic plan and processes, cloud-based big data	Sophisticated, enterprise-wide big data and analytics architecture, cognitive technologies, prescriptive and autonomous analytics
Analytical techniques	Mostly ad hoc, simple math, extrapolation, trending	Basic statistics, segmentation, database querying, tabulations of key metrics are leveraged to gain insights	Simple predictive analytics, classification and clustering; dynamic forecasts	Advanced predictive methods deployed to discover insights; advanced optimization, sentiment analytics, text and image analytics	Neural nets and deep learning, genetic algorithms, advanced machine learning

Processes and Programs. Fact-based analyses often require process and program changes to yield results. For example, insights into the best way to persuade wireless customers not to defect to another carrier need to be translated into actions—such as developing a new program to train customer-facing employees.

One way to ensure that insights are incorporated into business processes is to integrate analytics into business applications and work processes. Incorporating analytical support applications into work processes helps employees accept the changes and improves standardization and use. For more advanced analytical competitors, automated decision-making applications can be a powerful way of leveraging strategic insights.

Products and Services. One of the best ways to add value with data is by creating innovative products and services that incorporate data and/or analytics; we described these in greater detail in chapter 3.

Road map to analytical competitor*

KSP 1 - 4

Stage 1 — Analytically impaired

An organization has some data and management interest in analytics

Managerial support: prove-it path

Stage 2 — Localized analytics

Functional management builds analytics momentum and executives' interest through application of basic analytics for selected use cases

Terminal stage: some companies' analytics efforts never receive management support and stall here as a result

Top management support: Full-steam-ahead path

Stage 3 — Analytical aspirations

Executives commit to analytics by aligning resources and setting a timetable to build a broad analytical capability

Stage 4 — Analytical companies

Enterprise-wide analytics capability under development; top executives view analytic capability as a corporate priority

Stage 5 — Analytical competitors

Organization routinely reaping benefits of its enterprise-wide analytics capability and focusing on continuous analytics renewal

	Full-steam-ahead path ⟷	*Prove-it path*
Management Sponsorship	Top general manager/CEO	Functional manager
Problem set	Strategic/distinctive capability	Local, tactical, wherever there's a sponsor
Measure/ demonstrate value	Metrics of organizational performance to analytics (e.g., revenue growth, profitability, shareholder value)	Metrics of project benefits: ROI, productivity gains, cost savings
Technology	Enterprise-wide	Proliferation of analytics tools, integration challenges
People	Centralized, highly elite, skilled	Isolated pockets of excellence
Process	Embedded in process, opportunity through integration supply/demand	Stand-alone or in functional silo
Culture	Enterprise-wide, large-scale change	Departmental/functional, early adopters

* See Davenport & Harris (2017, pp. 159 - 183)

Big Data has the potential to reveal drivers for long term value creation

KSP 3

Endogenous and Exogenous ESG Data Sources

Source: Cheong et al. (2022, p. 9)

Framework for the application of data analytics for managerial accounting*

KSP 5 - 6

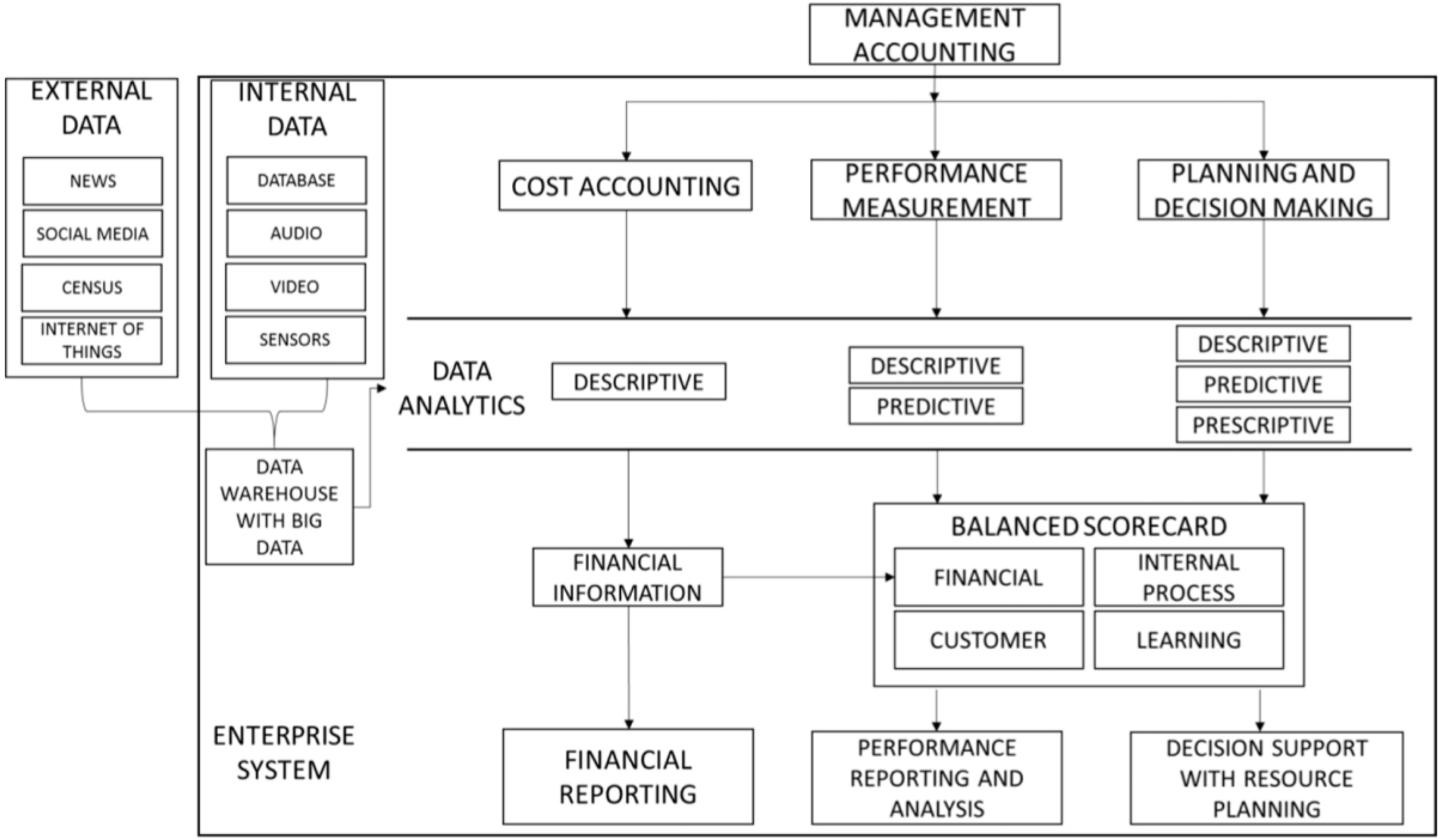


Fig. 1. The Managerial Accounting Data Analytics (MADA) framework, motivated from Cokins, 2013, pg. 27.

* See Appelbaum et al. (2017). Figure 1 (excerpt from p. 35) summarizes the framework.

Relevant analytical techniques for management accounting*

KSP 5 - 6

Predictive

- Analytical Hierarchy Processes (AHP)
- Artificial Neural Networks (ANN)
- Auto Regressive Integrated Moving Average (ARIMA)
- Bagging and Boosting models
- Bayesian Theory/Bayesian Belief Networks (BBN)
- **Benford's Law**
- **Classification (e.g., J48/C4.5, Random Forest)**
- Dempster-Shafer Theory Models
- Expert Systems/Decision Aids
- Genetic Algorithms
- **Hypothesis Evaluations**
- **Linear univariate and multivariate Regression**
- **Logit and Probit Regression**
- **Markov chains**
- **Monte Carlo Simulation**
- Multi-criteria Decision Aid
- **Nonlinear Regression**
- Probability Theory Models
- Process Mining: Process Optimizations
- Structural (Equation) Models
- Support Vector Machines (SVM)
- **Time Series (besides ARIMA)**

Descriptive

- Clustering Models
- **Descriptive Statistics**
- Process Mining: Process Discovery Models Ratio Analysis
- **Correlation Measurement**
- Text Mining Models
- Visualization
- **Exploratory Factor Analysis**

Prescriptive

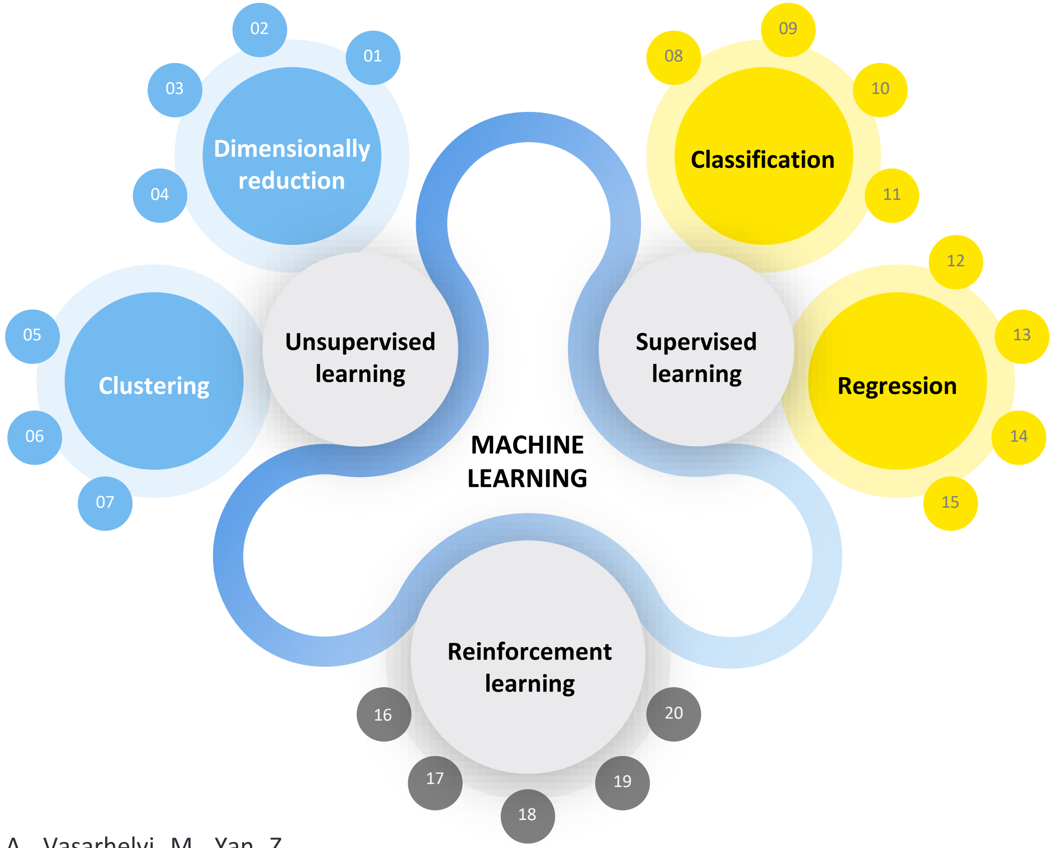
- **ANN**
- ARIMA
- Expert Systems/Decision Aids
- Genetic Algorithms
- **Linear Regression**
- **Logit and Probit Regression**
- **Markov chains**
- **Monte Carlo Simulation**
- **Nonlinear Regression**
- **Programming (linear-nonlinear, static-dynamic, deterministic-probabilistic)**
- **Time Series (besides ARIMA)**

* This overview builds on Table 2 in Appelbaum et al. (2017, p. 38)

Explanatory and predictive analytics for business performance management

KSP 5 - 6

01. Feature Elicitation
02. Structure Discovery
03. Meaningful compression
04. Big data Visualisation
05. Recommended Systems
06. Targeted Marketing
07. Customer Segmentation



08. Fraud Detection
09. Image Classification
10. Customer Retention
11. Credit Risk, Payments & Business Failure
12. Forecasting
13. Predictions
14. Process Optimization
15. New Insights

16. Real-Time Decisions
17. Game AI
18. Learning Tasks
19. Skill Acquisition
20. Robot Navigation

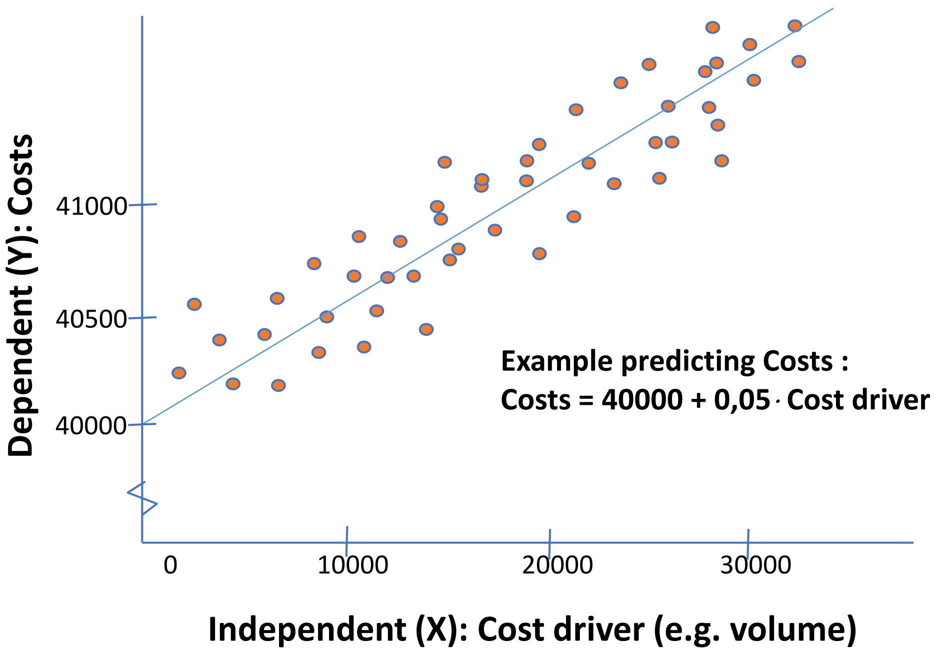
Sources: (1) Appelbaum, D., Kogan, A., Vasarhelyi, M., Yan, Z., 2017. Impact of Business Analytics and Enterprise Systems on Managerial Accounting. *International Journal of Accounting Information Systems*. 25: 29-44. (2) Bhimani, A., Willcocks, L., 2014. Digitisation, 'Big Data' and the transformation of accounting information. *Accounting and Business Research*. 44(4): 409–490. (3) Roozen, F., Steens, B., Spoor, L. 2019. Technology: Transforming the Finance Function and the Competencies Management Accountants Need. *Management Accounting Quarterly*. 21(4): 1-14.

Purpose: Explaining and predicting a dependent variable

Key technical backgrounds

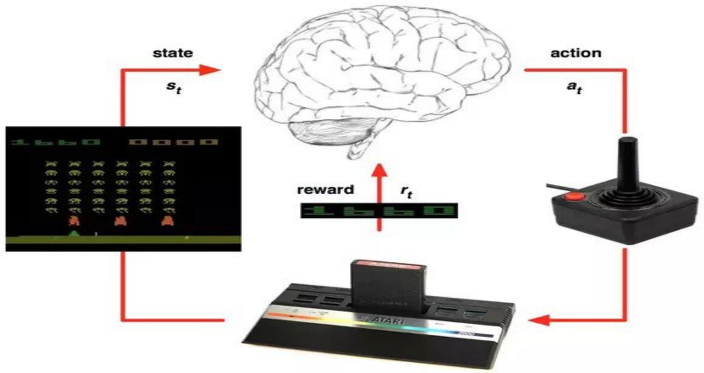
- **Regression analysis:** applied for estimating a model of independent/explanatory variable(s) ($X_{i,j}$) and dependent variable(s) (y_i)
- **Regression model**: $y_i = c_{i,0} + c_{i,1} \cdot X_{i,1} + \ldots + c_{i,k} \cdot X_{i,k} + \varepsilon_i$, $i = 1, .., n$
- **Purpose**: define relation between performance metrics and drivers by finding un-biased, consistent and efficient estimates for the coefficients $c_{i,j}$
- **Significance** is measured by adjusted R^2, F-value of the model and T-values of the coefficients and corresponding p-values indicate significance level
- **Robustness** refers to meeting conditions (a/o homoscedasticity, normality, autocorrelation, multicollinearity, linearity)
- **Predictive performance:** requires significance and robustness and is measured by MSE, RMSE, RSE, Accuracy, AUC for data not applied for estimating model
- **Logit and probit regression**, for explaining and predicting binary (0-1) dependents or the probability of each outcome (e.g., for predicting *financial distress, loan defaults, contractual breaches, customer churn, employee attrition);* specific significance, robustness and predictive performance statistics are used; see also under classification

Example:

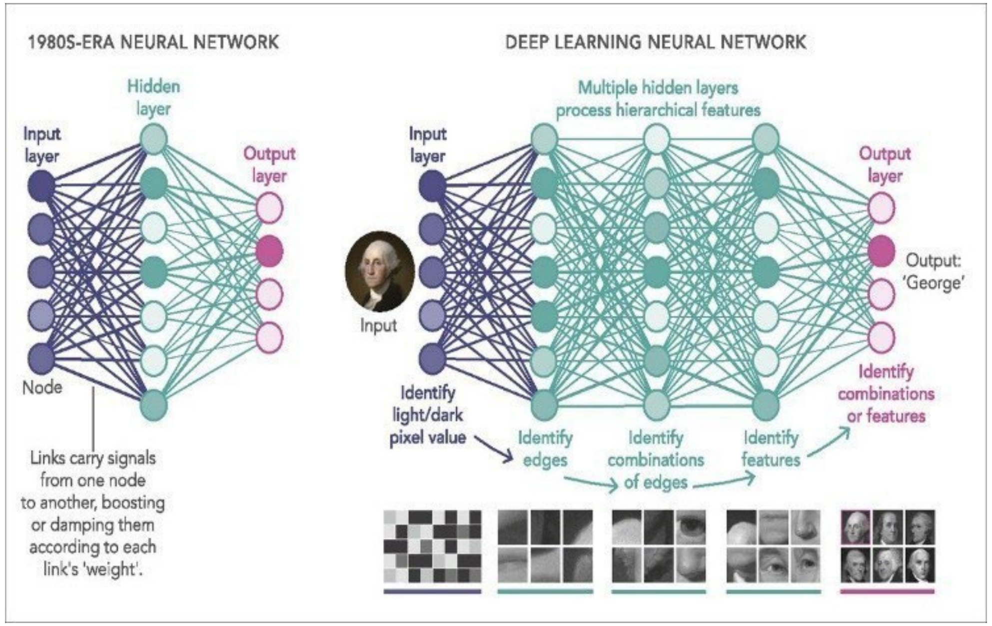


Supervised and unsupervised learning

- **Supervised learning**: algorithm learns from example data for the input variables (x) and output variable (y) and associated target responses for the output variable (y) in order to later predict the correct response for new examples
- **Reinforcement learning**: enhances supervised learning by giving positive feedback (rewards) or negative feedback (penalties) during the learning process
- Most ML applications use supervised learning based on **Regression** or **Classification**
- **Unsupervised learning**: algorithm learns from plain examples without associated response, leaving it to the algorithm to determine data patterns on its own, based input data (x) only
- **Association learning**: allows the AI system to discover any relevant structure in the data by **Clustering** or **Association**



Deep learning

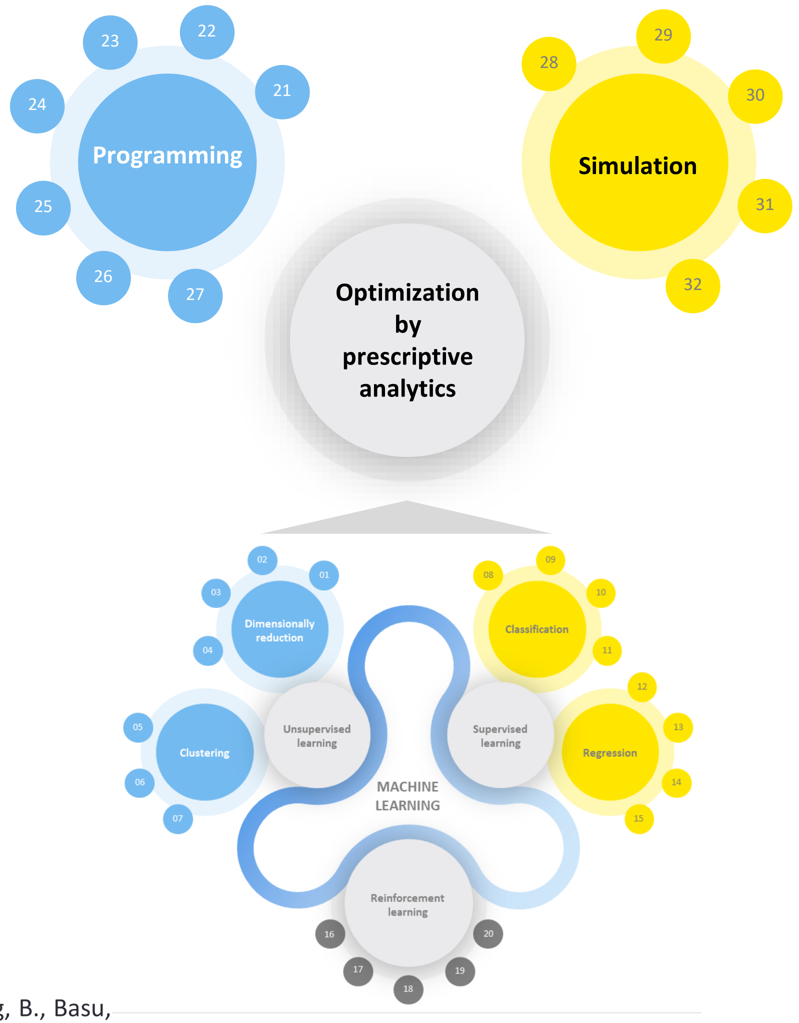


Dog or muffin?

Prescriptive analytics for business performance management complete the suite of analytic techniques

KSP 5 - 6

21. Network modelling
22. Combinatorial models
23. Linear programming
24. Non-linear programming
25. Dynamic programming
26. Probabilistic programming
27. Mathematical programming

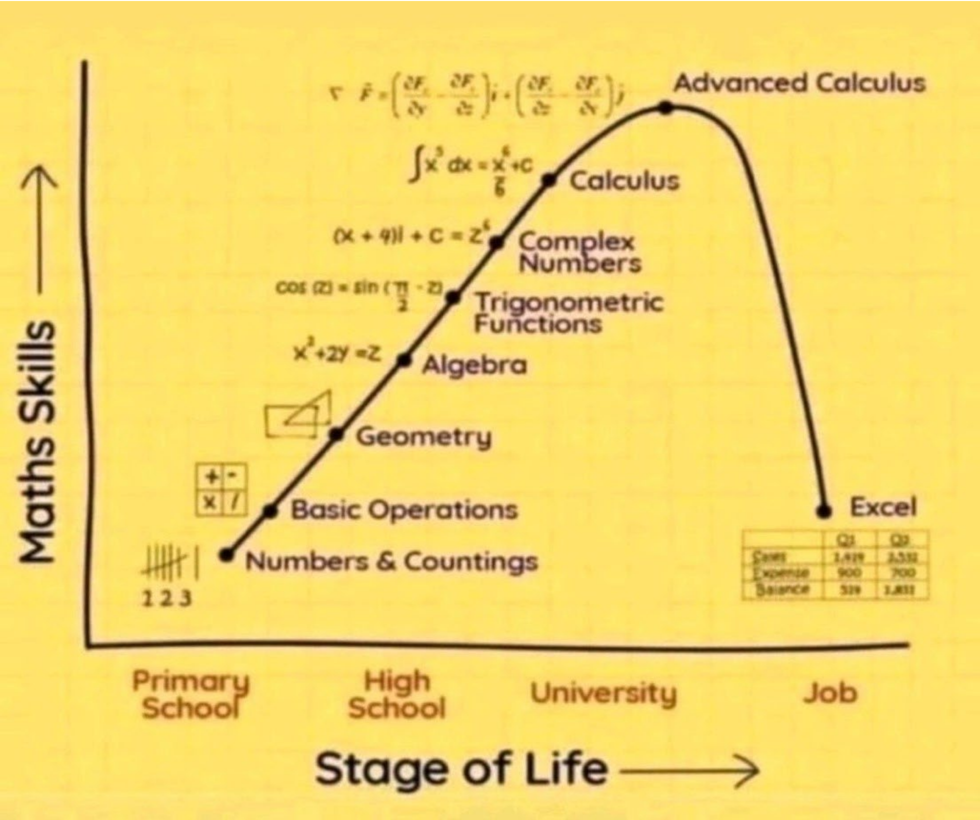


28. Analytical simulation modelling
29. Deterministic simulation
30. Monte Carlo Simulation
31. Markov Chain
32. Waiting line modelling

Source: Hillier, F.S., Lieberman, G.J., Nag, B., Basu, P. 2017. *Introduction to Operations Research*, 10th Edition, McGraw Hill Education

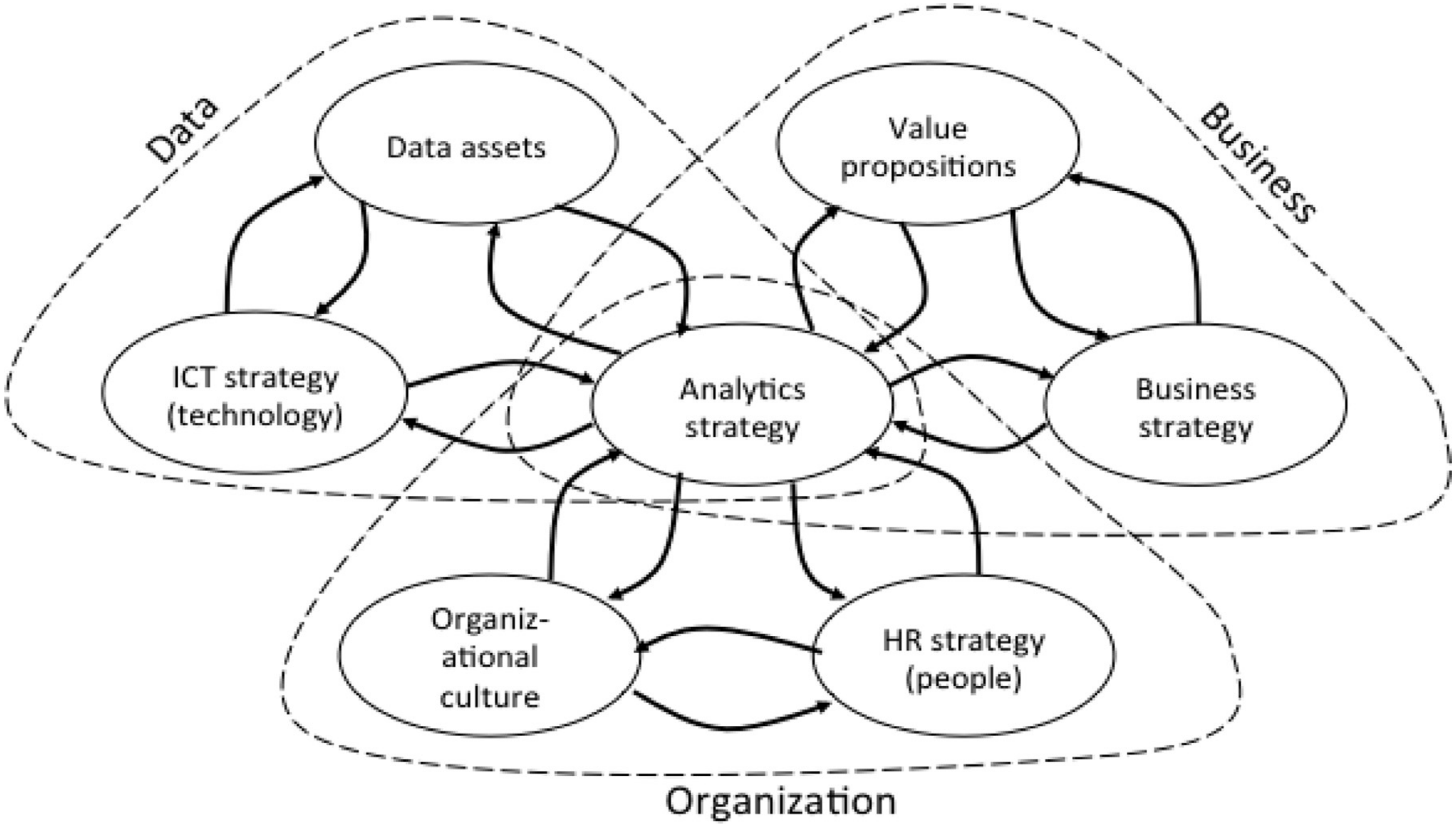
Mathematics and statistics: also relevant for financial professionals in their business partner role

KSP 6



Business analytics as a coevolving ecosystem*

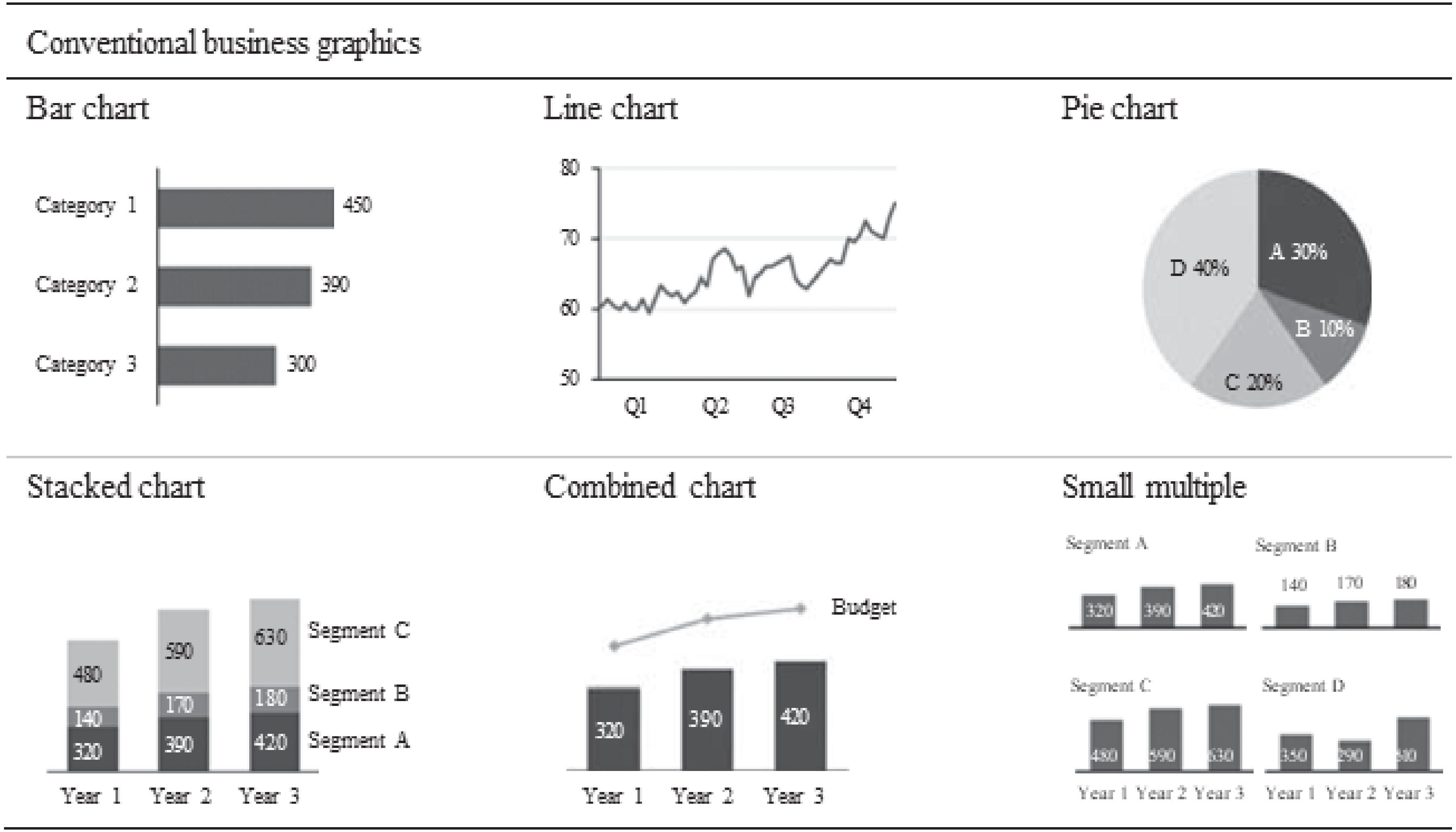
KSP 7



* See Vidgen et al. (2017, p. 635)

Visualizations used in every day life (type I visualizations)

KSP 8 - 9



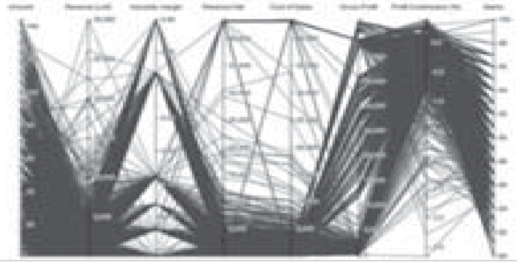
Source: Perkhofer, L.M., Hofer, P., Walchshofer, C., Plank, T., Jetter, H., 2019. Interactive visualization of big data in the field of accounting: A survey of current practice and potential barriers for adoption. *Journal of Applied Accounting Research*. 20(4): 497-525..

Visualizations designed to cope with large structured and unstructured data sets, including big data (type II visualizations)

KSP 8 - 9

Multidimensional visualization

Parallel coordinates

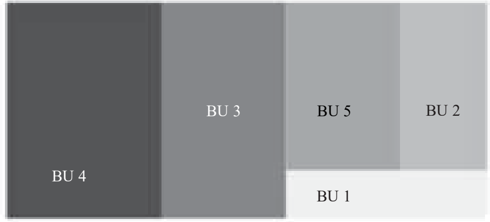


Sankey

Sunburst

Hierarchical and network visualizations

Treemap



Tree Visualization

Force-Directed Graph

Text and geographical visualizations

Word Cloud

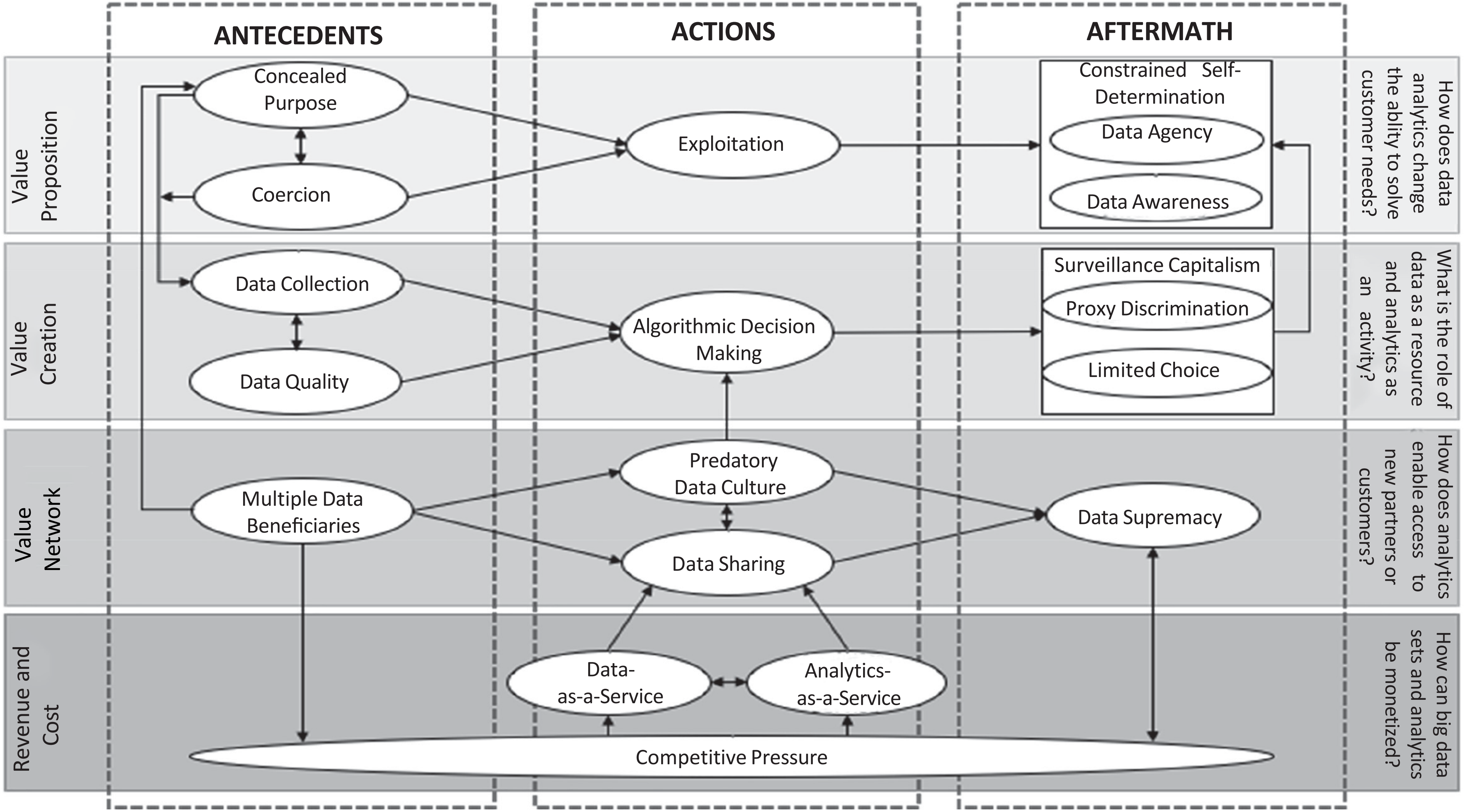
Map1

Map2

Source: Perkhofer et al. (2019).

Business controllers need to understand and deal with ethical challenges of data-driven business models

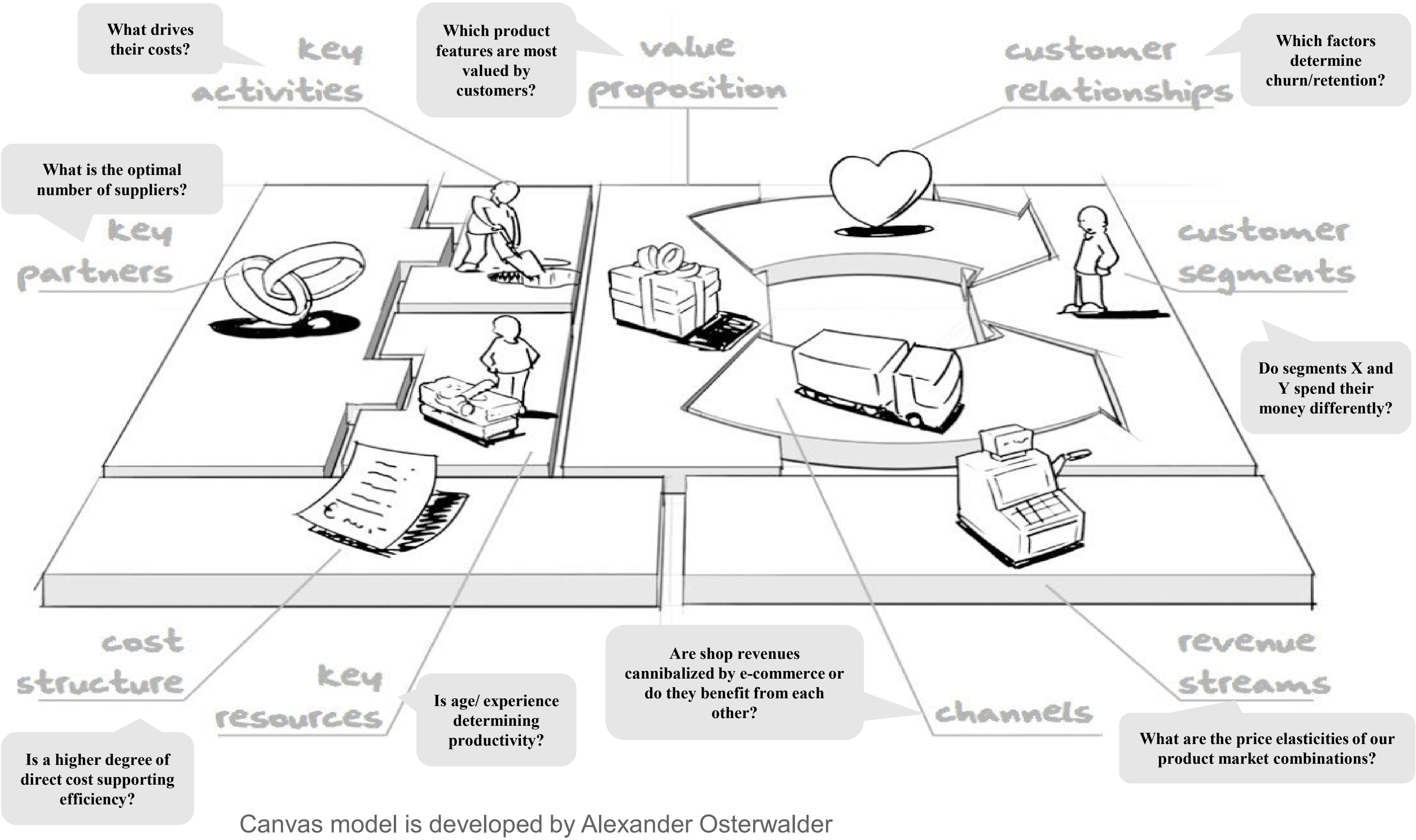
KSP 7 + 9



Source: Breidbach, C.F., Maglio, P. (2020). Accountable algorithms? The ethical implications of data-driven business models. *Journal of Service Management*. 31(2): 163-185.

Business analytics: for testing and substantiating claimed features of the business model or to answer related questions (and comprise financial analytics)

KSP 9

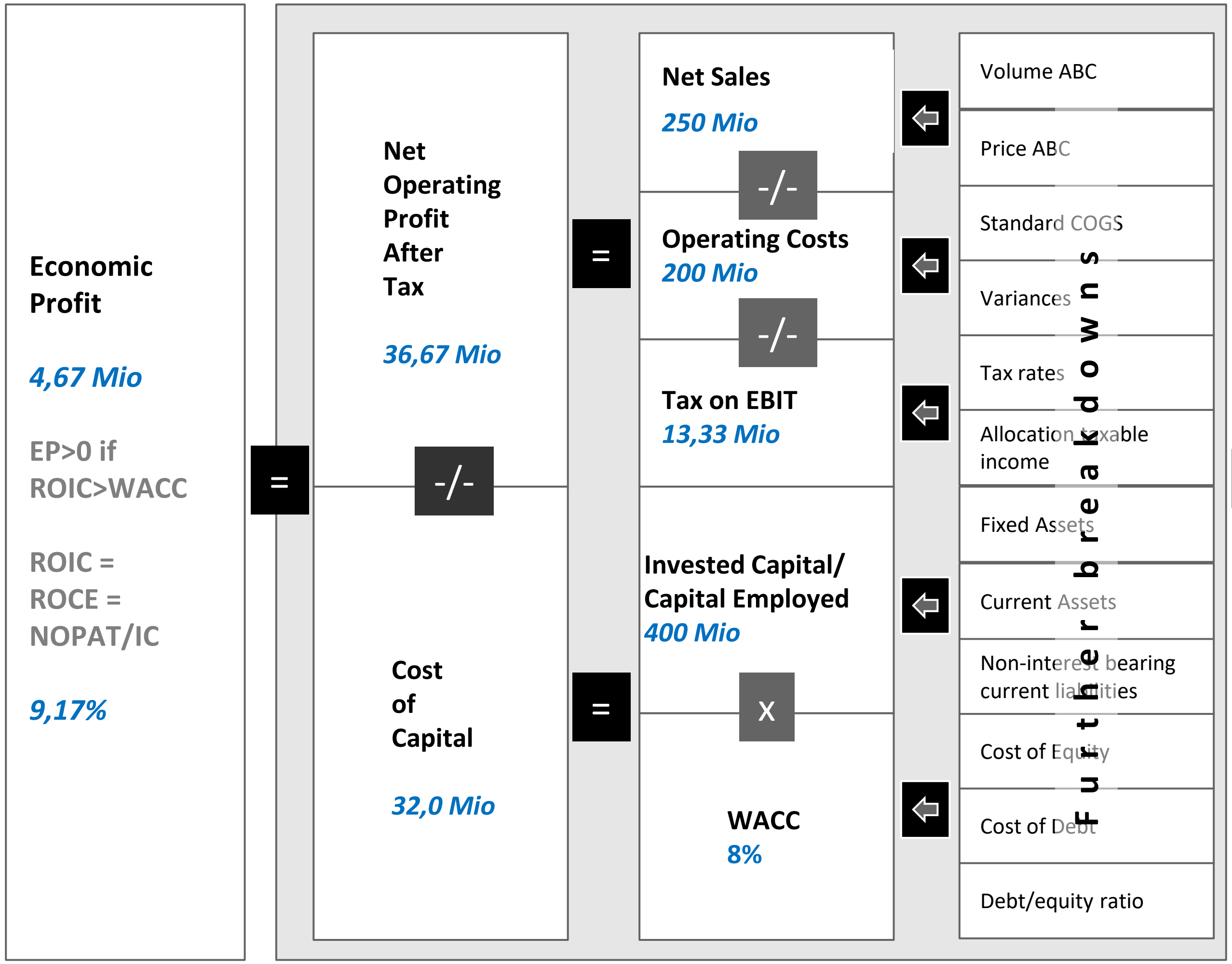


Canvas model is developed by Alexander Osterwalder en Yves Pigneur, 2010.

Financial analytics are used to establish influences of financial and non-financial value drivers on profitability, cash flows, assets and liabilities

KSP 9

Value tree - EP



Value drivers

Financial

- Items in value tree
- Return on invested capital
- Growth
- Net investments
- Investment rate
- Days sales outstanding
- Days sales in inventory
- Financial risk profile
- Financing defaults
- Corporate income tax
- VAT
- Custom duties
- Excise duties
- Et cetera

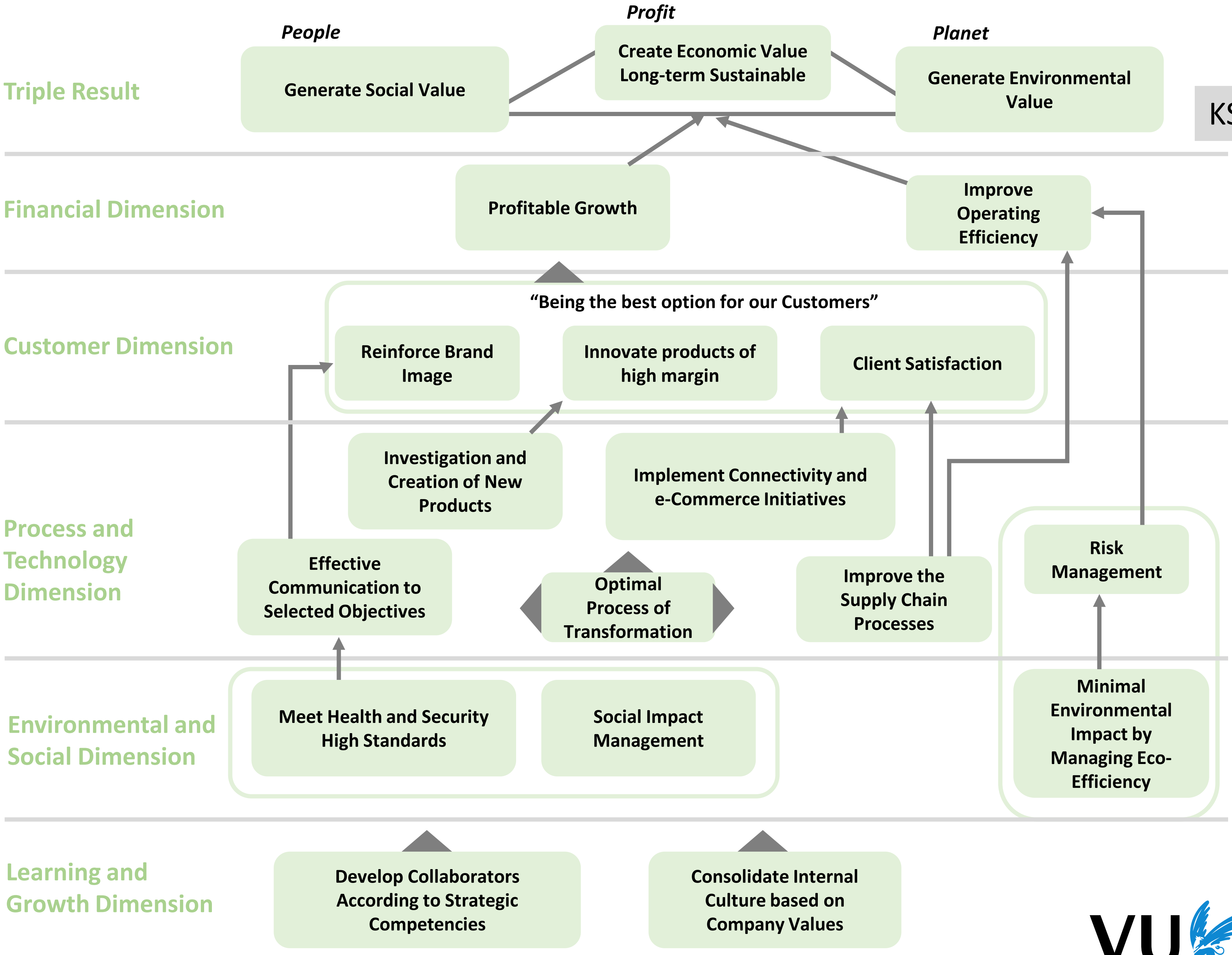
Non Financial

- Time to market
- Complexity of portfolio
- Complexity of products
- Complexity of processes
- Direct measures of costs
- Customer satisfaction
- Customer retention
- Delivery reliability
- Quality of processes
- Quality of outputs
- Insight in developments
- Quality of networks
- Reputation
- Et cetera

Source: Steens (2016), p. C1811-5

TBL-BSC

Example of simultaneous integration of economic, environmental and social objectives in strategy map at investment holding company specialized in the business of forestry and wood derivatives



KSP 9

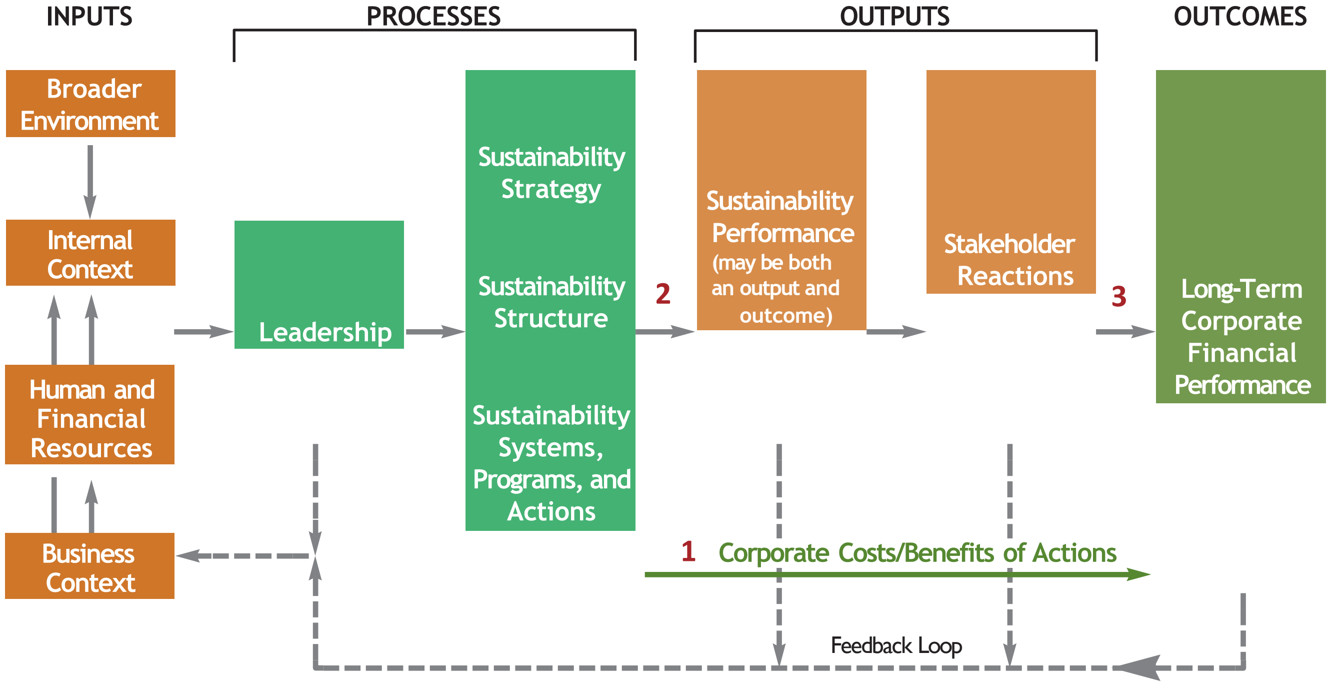
Are modelled causal relations based on evidence?

Corporate Sustainability Model

Are modelled causal relations based on evidence?

KSP 9

Source: Epstein and Buhovac (2014)



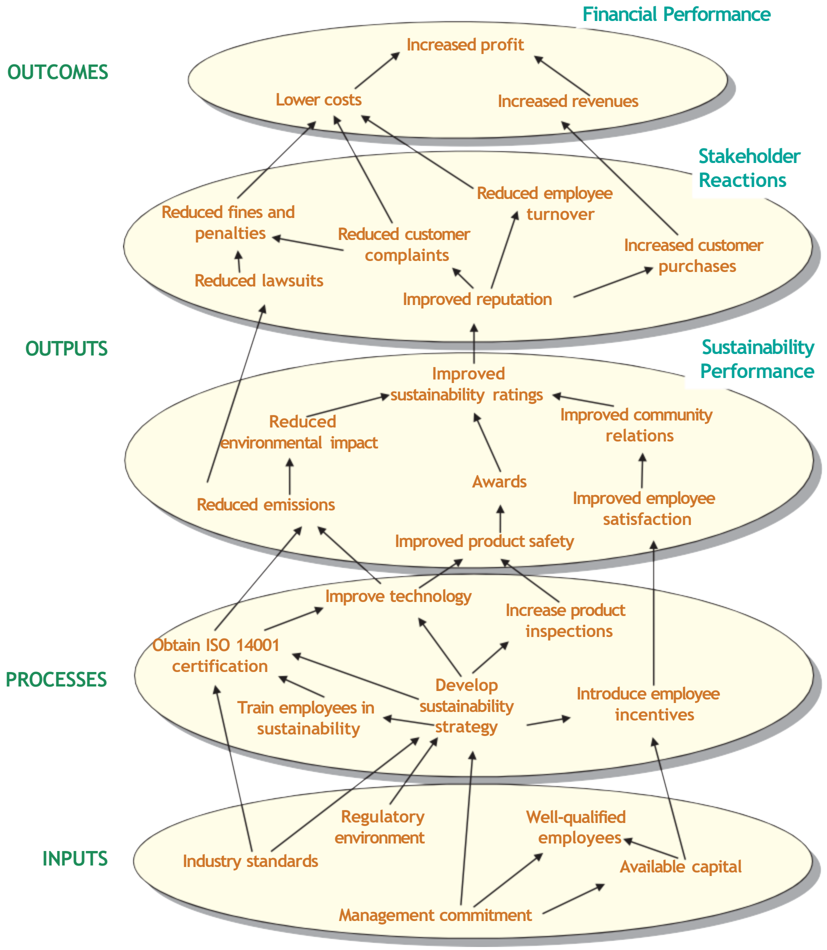
There are three major sets of impacts:

1 Corporate Costs/Benefits of Actions

2 Social, Environmental, and Economic Impacts

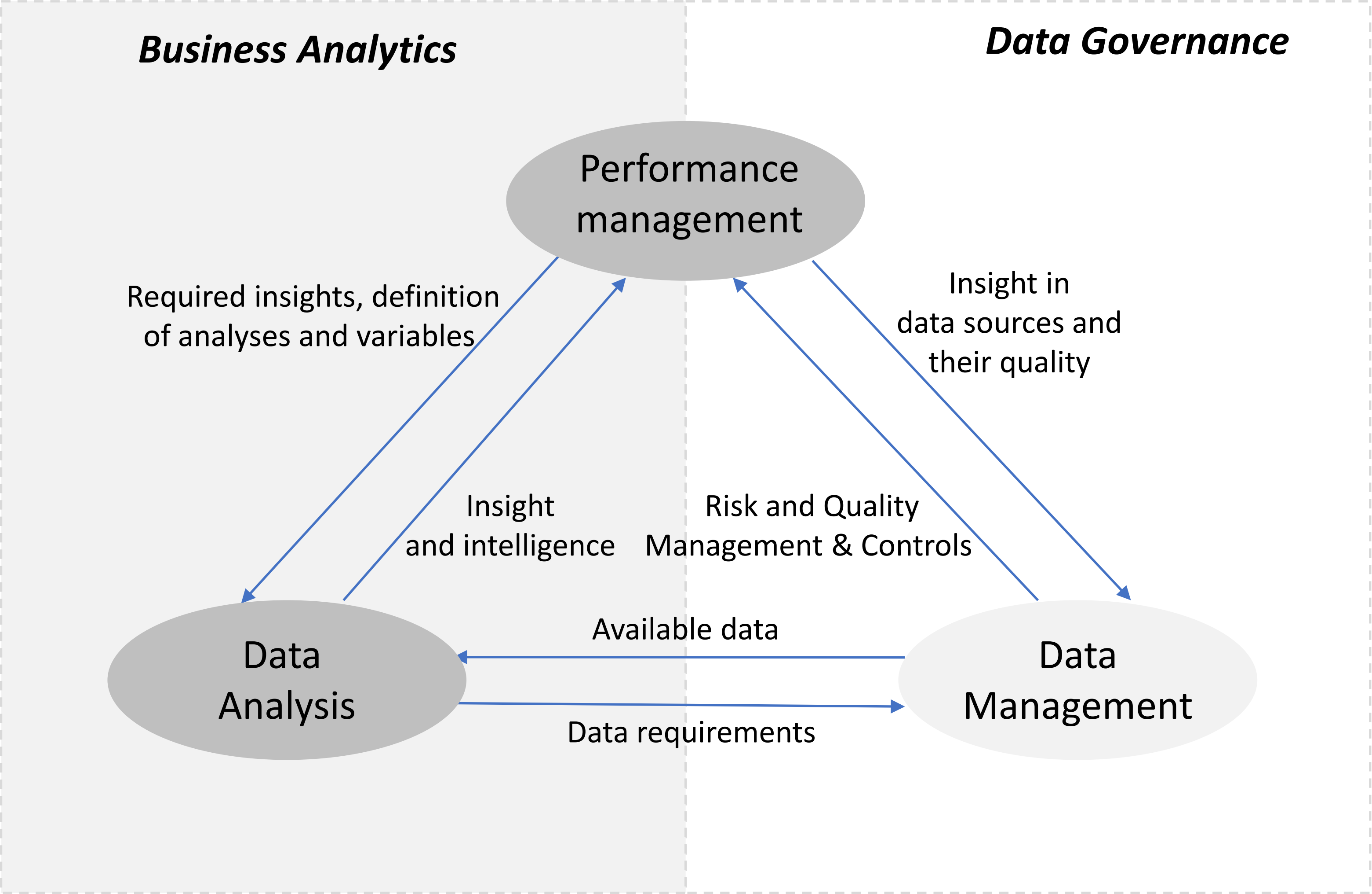
3 Financial Impact through Sustainability Performance

Source: Marc J. Epstein, *Making Sustainability Work: Best Practices in Managing and Measuring Corporate Social, Environmental, and Economic Impacts*, Greenleaf Publishing Limited, Sheffield, England, and Berrett- Koehler Publishers, Inc., San Francisco, Calif., 2008.



Gaining business intelligence demands from financial executives a solid vision on the required insights and how to get these insights using data and analytics

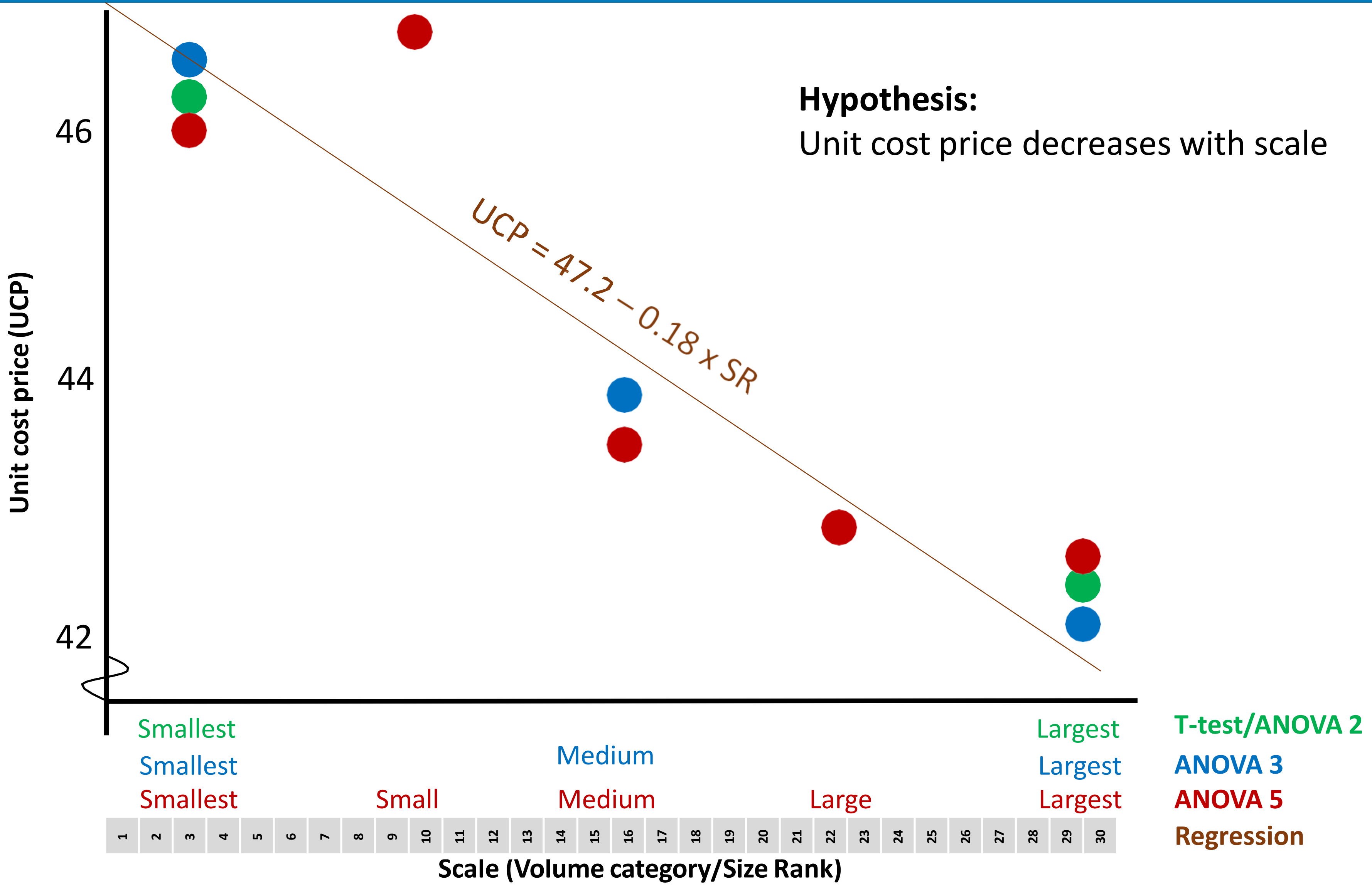
KSP 9



Impression video 2 (available via website)

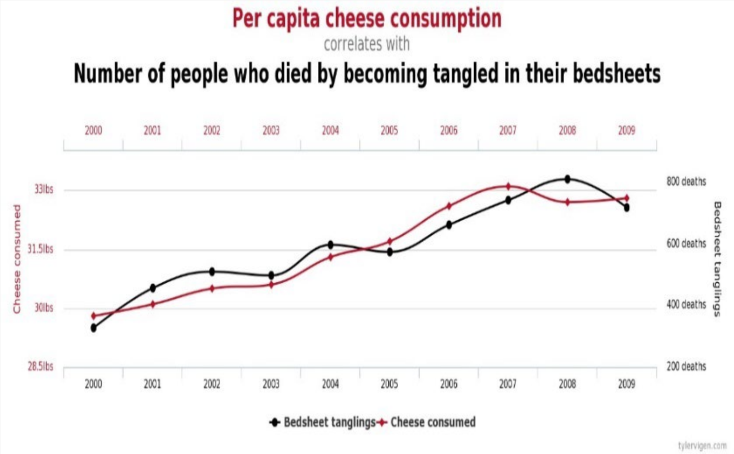
3. Explanatory & predictive regression-based analytics

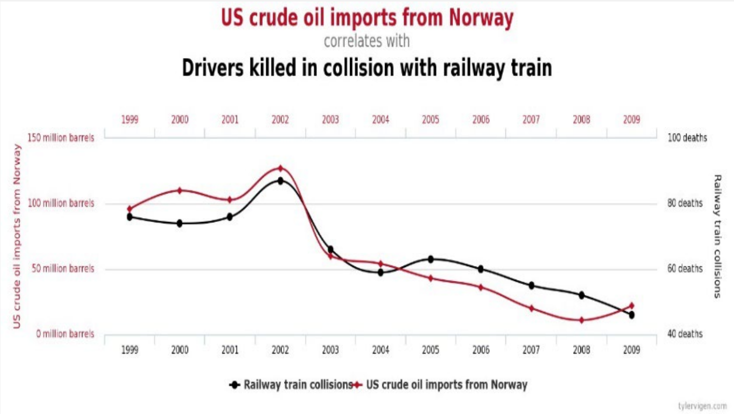
Comparison of t-test, Anova and regression



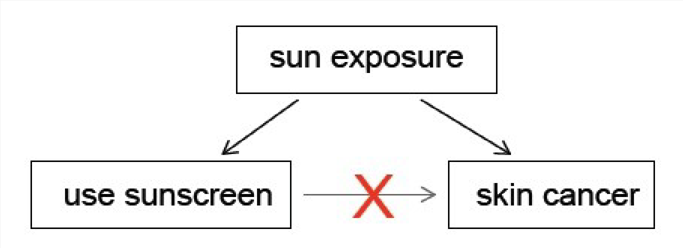
Statistics: please handle with care!

Spurious correlations





Incorrect inferences



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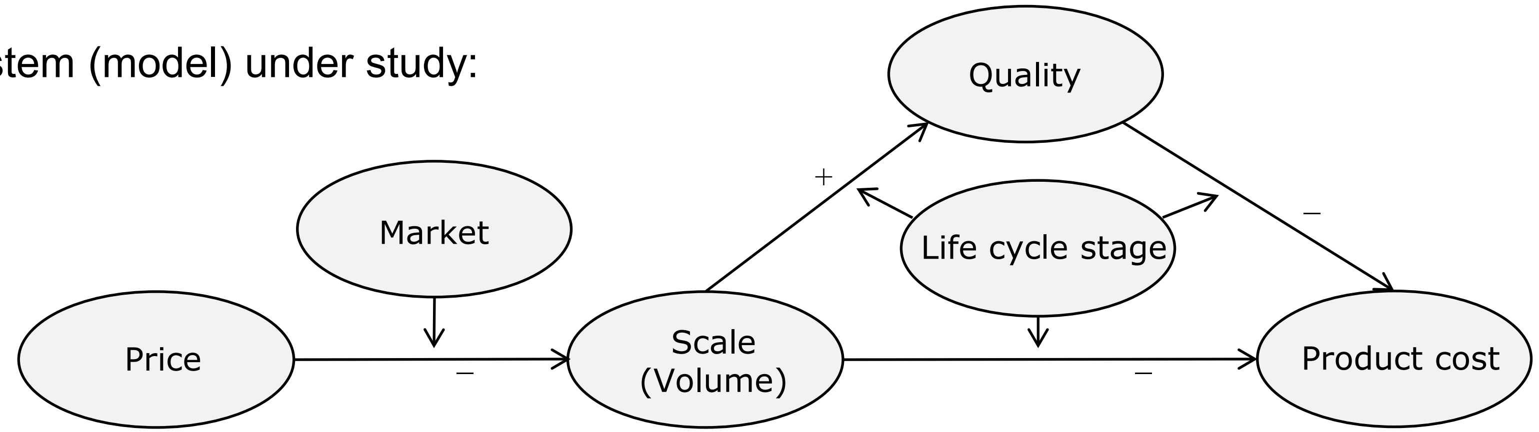
Applying explanatory and predictive analytics starts with modelling the problem (using variables and their interrelations)

- ‘Variable’ is defined as a characteristic/feature of the subject or object under study
- A variable is also an element of the ‘system’ under study (variables and their relations)
- The term ‘variable’ is consistent with the usually dynamic character of the setting under study and mutual influences of the variables
- Example problem statement:

  “We have insufficient insight in the impact of quality and scale on our product costs. Therefore, we do not know whether we perform in accordance with our differentiation strategy for new product market combinations and our low cost strategy for our mature business.”
- Variables: scale (volume), quality, product cost, life cycle stage
- System (model) under study:



For testing hypotheses the variables, the relations and the statistical tests need to be operationalized

- Variables are operationalized by means of concrete definitions and consistent data
- Data are obtained from existing systems and databases ('archival data'), surveys, interviews, experiments and simulations
- Relations are operationalized by 'direction', conditions (e.g., within which range is the hypothesis relevant), determinants (factors that determine the relation, such as seasonal patterns) and control variables (e.g., age, gender, experience)
- The test is selected based on the variables, the data (normal distributed?) and the assumed relationships (linear, non-linear, category-specific, et cetera)
- A relationship is expressed by a function of a dependent variable of the independent variable(s): $Y = f(X_1,.., X_n)$; the function f determines (a/o) the impact of each X_i on Y
- Mediation and interaction effects can be relevant for accurately determining the impacts; for instance:
  - A particular impact can depend on the geography, the type of industry, the company size, product life cycle stage et cetera (interaction)
  - A particular impact can involve a direct impact (of the independent variable on the dependent variable) and an indirect impact (of the independent variable on the dependent variable through another independent variable) (mediation)

Generic steps (1/2)

1. Select a use case and define the expectations/hypotheses based on the setting, management insight and already existing research findings (to the extent available)

2. Express expectations/hypotheses in terms of the variables and the relations between the variables (mostly cause-and-effect relations)

3. Determine the data set, gather the data and capture them by means of an adequately structured database/file; document the data set by means of descriptive statistics

4. Operationalize the variables and their relations (hypotheses) by means of definitions that are consistent with existing research and available source data

5. Operationalize the statistical tests and substantiate the selected tests

6. Evaluate the chosen set-up of the empirical research based on common criteria: reliability of data, reliability of research method, internal validity and external validity, and causality.

Generic steps (2/2)

7. Identify correlations between variables (by means of the correlation table)

8. Execute the relevant tests and document the outcomes in detail

9. Test the robustness of the outcomes by testing the required conditions and criteria and by varying the model specifications

10. Analyze and evaluate the outcomes from the perspective of the hypotheses and draw conclusions regarding the acceptance or rejection of the hypotheses

11. Draw conclusions on the relevance of the outcomes (based on 10) and the limitations (relating to the data and the research method) and define suggestions for further research

12. Communicate the findings and develop reports per target group (use visualization), and put the outcomes into action, e.g., by administering measures, applying substantiated relations between variables for forecasting models (this requires historical tracking), using outcomes as basis for machine learning or optimization/improvement

Some examples of hypotheses that are candidates for use cases based on regression analysis

- An increase of the consumer price for product x in market y decreases the volumes and increases the sales
- The price elasticity of product x in market y ranges between -1 and 0
- The profit margin (ROS) of customers of segment X is x% higher than those of segment Y
- The churn of customers is higher when the price is higher and the client satisfaction score is lower
- The working capital level is determined by sales and type of customer
- The sales volumes develop more favorably when inventories are higher
- The sales volumes develop more favorably when delivery times are shorter
- A decrease of temporary labor is an early warning signal for decreasing sales of production companies the next quarter
- The productivity of a team is a function of the size of the team and the average age of the team
- The number of accounts of the SCoA and the number of budget iterations determine the costs of the finance function

4. Case Car USA

During the experience session an example was provided
(analytics application and key criteria for evaluating outcomes)

Impression video 3 (available via website)

5. Q&A

Thank you for your attention!