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Preparing students for careers using business analytics and data-driven decision making

Erland Hejn Nielsen and Steen Nielsen

AARHUS BSS
DEPARTMENT OF ECONOMICS
AND BUSINESS ECONOMICS
AARHUS UNIVERSITY

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Erland Hejn Nielsen and Steen Nielsen

Department of Economics and Business Economics, Aarhus University, Denmark. Section for Econometrics and Business Analytics.

Abstract

Data analytics and performance measurement and management (PM&M) now seem to be deeply rooted disciplines for both professional decision makers and in the business environments. Research articles and consulting companies (e.g., AACSB, 2014) stress the importance of recruiting students with a proficiency in business analytics and of preparing students with knowledge, skills, and ability in the area of business analytics (BA) and machine learning, as these skills will help businesses process data, find patterns and relations, and make decisions and predictions. However, several ideas from BA actually go back to Anthony and Harvard Business School in 1965 and to Tukey and Princeton University in 1962, respectively. The purpose of this paper is first to discuss and show the use of BA for performance management models and decisions. Second, we discuss the content of PM&M and all the uncertainty that surrounds it. Third, we show how to combine BA and PM&M in a bachelor course, and finally we discuss the assumptions and skills necessary for students in relation to completing such a course. In this sense, the nature of our paper is inspirational. Finally, the paper reports the result from a survey made among the students who have taken the course, that is, that students' interest in data-driven performance is best activated through a combination of hands-on learning and inspirational datasets.

Keywords: *Performance measurement and management, quantitative models, business analytics, Monte Carlo simulation, data-driven decisions, system dynamics, algorithms, flow and stock.*

JEL Classification: A22, C81

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A. Introduction

The emergence of the 'Age of Data' has opened a new chapter within data processing. Data can be a weapon in the war of economics. However, best practices (Measurement Leaders) treat KPIs differently than other. Rather than focusing exclusively on how KPIs can help them manage their organization, Best Practices look to KPIs to help them lead — to find new growth opportunities for their company and new ways to motivate and inspire their teams (Marr, 2018; Schrage, 2019). According to the survey of Schrage and Kiron (2018), best practices set themselves apart in the following ways. They use KPIs to lead, as well as manage, they pursue a holistic view of the customer, they see KPIs as datasets for machine learning, they insist on the ability digitally to drill down to KPI components, they share trusted KPI data, and they aim for KPI parsimony — determining which KPIs are most vital and valuable. The same companies also describe their organization as 'mostly data-driven' or 'predominantly data-driven'.

Successful management of a modern company requires more than performance measures per se (Melnyk *et al.*, 2014). The importance of integrating Business Analytics (BA) and Performance Measurement & Management (PM&M) with strategy has also been an important topic and has been emphasized within the last teen years (see e.g., Accenture, 2017; Gartner, 2012, 2013; Gashgari, 2015; Genpart and Future Group, 2017; New Vantage Partners, 2018; Warren, 2004). These topics have also been discussed in relation to different job profiles (Deloitte, 2015; Lawson, 2018; McKinsey, 2013), but have also been criticized (see e.g., Kaiser and Young, 2018).

Data analysis is part of the concept of 'data science', which was originally proposed within the statistics and mathematics community (Tukey, 1962). Data science, on the other hand, is a new interdisciplinary field that builds on and synthesizes a number of relevant disciplines and bodies of knowledge, such as statistics, informatics, computing, communication, machine learning, management, and sociology, to study data and its domain following a data science line of thinking (Cao, 2016).

Data analysis deals extensively with visualization, such as box plots, histograms, multi-vari chart, scatter plots, and stem-and-leaf plots etc. (see e.g. Chap. 2 in Hair *et al.*, 1998 and Tabachnick and Fidell, 2007). A recent New York Times article (2018.01.24)) also discovers the 80-20 rule: that 80% of the time a typical data science project is sourcing, cleaning, scaling methods (normalization and standardization), and preparing the data, while the remaining 20% is actual data analysis[1].

The benefits of data-driven decision-making have been documented conclusively. Brynjolfsson *et al.* (2011) from MIT conducted a study of how data-driven decisions affect firm performance. They developed a measure of data-driven decisions that rates firms depending on the extent to which they use data to make decisions across the company. They demonstrate that statistically, the more data driven a firm is, the more productive it is—even controlling for a wide range of possibly confounding factors. Besides, the differences are significant. One standard deviation higher on the data-driven decisions scale is associated with a 4% – 6% increase in productivity. Data-driven decisions also correlates with higher return on assets, return on equity, asset utilization, and market value, and these relationships seem to be causal. The important question a company should ask itself is: *"What can we do that we couldn't do before, or do better than we could do it before?"*

The primary purpose of this paper is to identify and discuss important elements of Business Analytics (BA) and performance management with the purpose of integrating the two in a teaching setup for bachelor students. More specific, the study addresses the impact of the data-driven decision-making evolution by investigating the knowledge, skills, and abilities (KSAs) needed within PM&M. Based on prior literature and

[1]See: http://blog.revolutionanalytics.com/2014/08/data-cleaning-is-a-critical-part-of-the-data-science-process.html
See also this for different stages: https://www.datasciencecentral.com/profiles/blogs/the-lifecycle-of-data

suggestions from research and teaching ideas, the study identifies a set of possible KSAs useful for helping students succeed in the evolving data-driven decision-making environment. Further, this paper shares key insights from a small survey based on a course on data-driven performance developed by the authors in order to put emphasis on and to provide opportunities for a more thorough integration of additional KSAs in a curriculum.

Building on literature from the field of analytics and performance, this study argues that the various aspects of data analytics should influence contemporary education curriculums and be integrated with performance management knowledge. Our main conclusion – from discussions with students and a small survey made among the students is - that data-driven modelling gives a 'new' and interesting way for the students to work with real problems.

We will use the 'validity network schema' (VNS) constructed by Brinberg and McGrath (1985) as the scheme for combining well-known topics and work elements in this paper. Brinberg and McGrach (1985) interpret empirical research as linking three domains—the substantive, the conceptual, and the methodological domains, but with the substantive domain as the focal and driving domain. Other kinds of research setups called 'research paths' are also presented, in which either the conceptual domain or the methodological domain is the main focus.

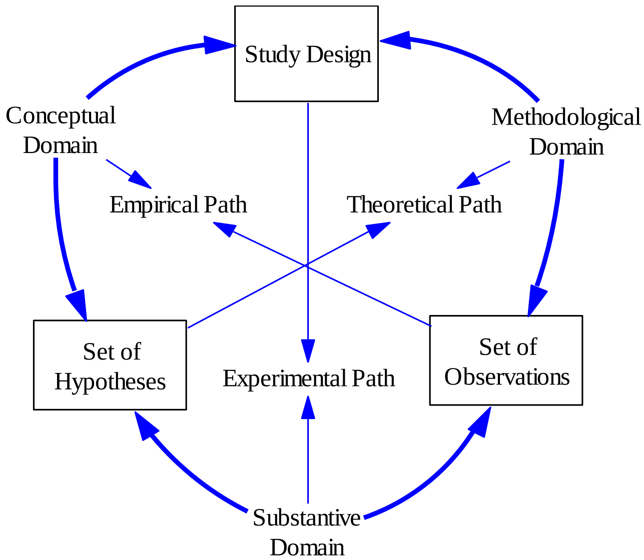

Figure 1: The validity network schema (VNS) developed by Brinberg and McGrath (1985)

The VNS identifies three prototypical, 'research orientations' for conducting an actual study. Three prototypical 'research orientations' are identified for conducting the study proper. Each of these orientations corresponds to one of the three domains for which the primary contribution is intended. The 'basic researcher' places his/hers primary emphasis on the conceptual domain, the 'applied researcher' desires to make statements about the substantive domain, and the 'technological researcher' aims to develop tools in the methodological domain. The present paper emphasizes the empirical path meaning, building a set of observations (datasets), and explaining them by construing them in terms of a set of meaningful concepts.

The organization of this paper is as follows. Section B, starts by looking at theory and on the trends for BA and DDM (Data-driven Modeling) based on the background and the related works including the VNS network schema. Section C then presents our teaching ideas elements and learning outcome to the course. Section D reports on some descriptive statistical results of a survey mad among the students who have completed the course together with a SEM (Structural Equation Model). Finally, the paper concludes the discussion together with future perspectives in section E.

B. From Performance Management System to Performance Management Analytics

The increasing demand for fact-based decisions and predictive information requires the use of data analytics and the ability to use different datasets and data views to fulfil such demands. A number of papers indicate that data analytics is being incorporated in university courses and that faculty actively integrate the subject in academic curriculums. Our paper is a contribution to existing literature on incorporating analytics and data-driven decisions into a performance measurement and management course program on the bachelor level.

Knowledge, Skills and Ability	*Examples of prior and inspirational literature*
Emphasising holistic performance models	Ahrens and Chapman (2007), Anthony (1965), Berry *et al.* (2009), Ferreira and Otley (2009), Kaplan (2010), Kaplan & Norton (2008), Accenture (2017), PwC (2013), Marr (2010; 2018).
Importance of data analytics	Brynjolfsson *et al.* (2011), Davenport & Harris (2007), Accenture (2017; 2013), Davenport & Kim (2013), AACSB (2014), Simchi-Levi (2014), Tukey, (1977), PwC (2015; 2017), CGMA & Oracle, (2015), CGMA (2016)
Implementing BA and BI	Baptiste (2018), Provost & Fawcett (2013), Gartner (2017), Gartner (2012), McKinsey Global Study (2017), Verbeke, W., Baesens and Bravo (2018),
Software usage (e.g. @Risk and SAS)	Albright and Winston (2017, book), Andiola *et al.*, (2020), Frownfelter- Lohrke, (2017), Emblemsvåg (2005), Evans (2013 book), Schriber, T. J. (2009), Togo (2004).
System dynamics for PM&M	Barnabè & Busco (2012), Norton (2000), Warren (2004), Nielsen & Nielsen (2012), Sterman (2000), Piersona & Sterman (2013)
Statistics & econometrics for decision-making and PM&M	Kaplan (IMA 2008), Ballou *et al.* (2018), Borthick *et al.* (2017), Campbell *et al.* (2015), Silvestro (2014), Klatt *et al.* (2013), Năstase and Stoica (2010), Perlman, (2013).

Table 1: inspirational and prior literature for our course

Data analytics denotes the knowledge and skills required for modelling and using big datasets for improving fact-based decision-making. Contrary to silo-based performance models, holistic performance models view an organization as an interconnected system in which a decision made in one department influences other departments and other people. Over the last 5-10 years, the combination ‘performance management and business analytics’ has become the subject of a huge number of articles and papers[2].

However, applying BA to performance management is still in its infancy. A number of studies and surveys do however emphasize this potential (e.g., Accenture, 2017; Gartner, 2012; PwC, 2017). We will briefly review a few of them below.

In a survey by Schrage and Kiron (2018), 70% of the executives use KPIs to lead and/or manage people and processes to a moderate or great extent. Not surprisingly, the most important KPIs relate to customers, for example customer lifetime value, NPS (Net Promoter Score) and brand equity, but with a growing recognition that KPIs must begin aligning internal processes with external customer behaviors. This emphasis on customers – and the understanding of customers in a more holistic way - is a shift towards measures beyond the traditional sales statistics (i.e., metrics earlier in the sales process and after purchase) (Schrage and Kiron, 2018).

That statistics and econometrics are now becoming part of the important tools for internal decision makers (often management accountants) can be seen from this citation from Kaplan in 2008 (In an interview with Paul Sharman in Strategic Finance): *“Management accounting analytics is no longer constrained by limited or complex access to companies’ databases. But to excel at analytics, management accountants will require extensive training in modelling, multivariate statistics, and econometrics”*.

[2]See for example: http://www.telfer.uottawa.ca/researchreport2014-15/outcomes-and-impact/business-analytics-and-performance-management
https://www.gartner.com/doc/2715117/business-intelligence-performance-management-key
https://www.youtube.com/watch?v=hxHT-0nD0gk
http://www.blog.corpeum.com/role-business-analytics-performance-management-part-2/

The AACSB (Association to Advance Collegiate Schools of Business) Standard A7 states the following: *"Consistent with mission, expected outcomes, and supporting strategies, accounting degree programs include learning experiences that develop skills and knowledge related to the integration of information technology in accounting and business. Included in these learning experiences is the development of skills and knowledge related to data creation, data sharing, data analytics, data mining, data reporting, and storage within and across organizations (Information Technology Skills and Knowledge for Accounting Graduates)"* (AACSB, 2014, p. 3).

In addition, PwC (2015) points to BA for undergraduate students by saying: *"Universities should infuse analytical exercises into existing curriculum to help students develop data analytics proficiency on top of their core accounting skills"* (PwC, 2015, p. 14). Later on: *"Statistical analytics course: providing students with an arsenal of tools in multivariate statistical analysis, including conjoint, cluster, discriminant function, and factor analysis"* (PwC, 2015, p. 15).

In addition, Norton has pointed specifically to System Dynamics by saying: "*Is Management finally ready for the 'Systems Approach'* and further*: Some critics of the Balanced Scorecard have complained that it creates unnecessary complexity. But as the creators of the systems approach to management argued 30 years ago, most businesses are by definition complex systems that require a management approach that can handle complexity"* (Norton, 2000).

Finally, in the IMA based journal 'Strategic Finance', an article 'BETTER PERFORMANCE THROUGH ANALYTICS' was published in October 2018 and an article 'MATH AND STATISTICS: THE SKILLS NEEDED IN MANAGEMENT ACCOUNTING' was published in December 2018. However, most classical textbooks within management accounting still do not include any discussion of BA (see e.g., Drury, 2017; Horngren *et al*., 2015) even though 'customer and customer profitability' and PM&M are important issues for management accounting for which analytical techniques and tools are required (Campbell *et al*., 2015, MITSloan Magazin, 2018; Nudurupati *et al*., 2016).

Figure 2 from Davenport & Harris (2017) shows the different steps and the degree of sophisticated intelligence that have inspired us. However, machine learning it not part of this course.

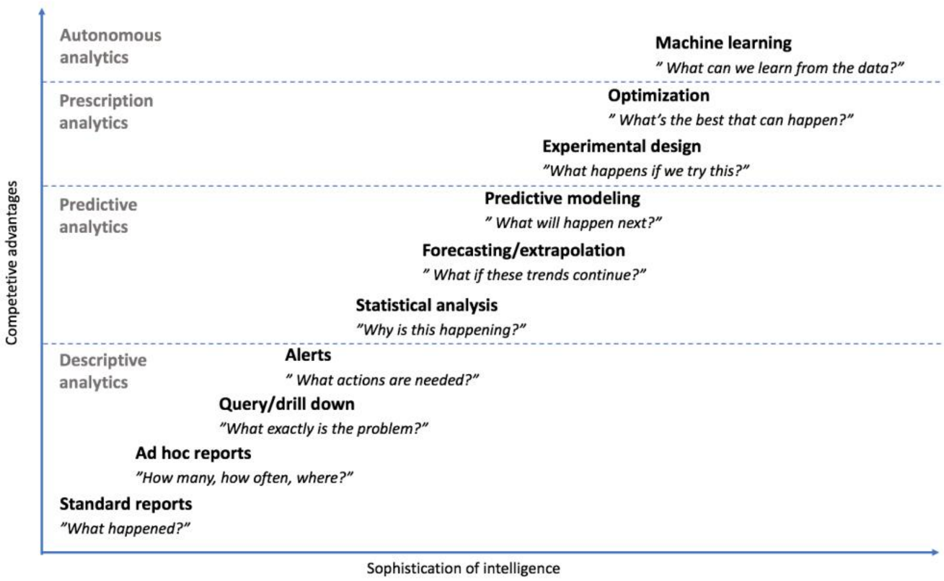

Figure 2: Potential competitive advantage increases with sophisticated analytics
Ref.: Davenport and Harris (2017)

Figure 2 puts a perspective on a company's level of sophistication ranging from descriptive analytics to machine learning. However, different companies are on different competitive levels, but should try to move up and not remain at the bottom of the chart. The ultimate goal of any analytics initiative is to effect change in the organization, which entails synthesizing all of the above analytics to create suggested courses of action.

However, prescriptive analytics is clear speculation about the future (e.g., "*we believe that reducing the lead time for customers will improve the satisfaction of customers, which again will improve our net profit*"). Nevertheless, prescriptive analytics is not possible without completing earlier steps of the analytics intelligence lather (Davenport and Harris, 2017). Finally, autonomous analytics employs artificial intelligence or cognitive technologies such as machine learning to create and improve models and learn from data with substantially less involvement by human analysts (Davenport and Harris, 2017).

Figure 3 is inspired by Klatt *et al.* (2011), Davenport and Harris (2007; 2017), the SAS-Institute (Haxholdt Presentation, 2007), Liberatore & Luo (2010), Appelbaum *et al.* (2017), Năstase and Stoica (2010), and Simchi-Levi (2014). It shows an APM (Analytics Performance Management) framework as the combination of three normally separate areas; accounting models and concepts, the content of business analytics, and different management science methods[3].

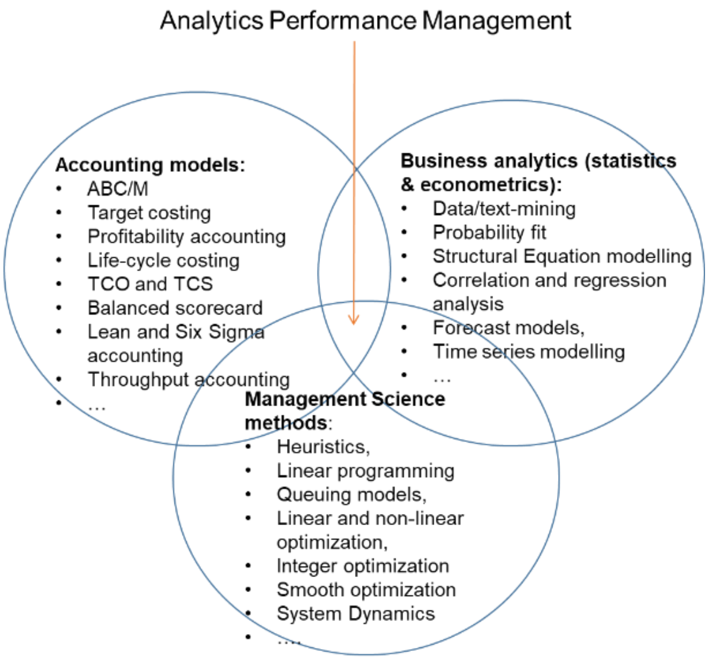

Figure 3: APM the intersection area of the three research areas

The purpose is to leverage analytics to deliver impact, benefit and value to the company. However, as pointed out repeatedly in the BA literature, 'soft values and intuition' are as important as the hardcore issues. Examples are understanding the business and giving data analytics a perspective (Davenport and Harris, 2007).

In the course, we have chosen BSC as our base model because BSC has a long history (starting with the HBR article by Kaplan and Norton in 1991) and because concepts and ideas have been continuously refined[4] (Capelo *et al.*, 2012). Besides, a lot of information about BSC can be found on most homepages of all big consulting companies (see e.g., McKinsey, Baan, SAS-Institute, IBM, Gartner, PwC). Finally, both Kaplan and Norton see BSC as a 'system' including all its assumptions for course-and-effect and qualitative and intangible assets. For example, measurement is an important assumption or as Kaplan (2010, p. 3) says:

[3]Other writers have used concepts such as "Performance Analytics" (Marr, 2010), or "Effective performance management analytics" (Klatt *et al.*, 2011).
[4]Since its inception in 2008, over 4000 delegates have registered for the programme, including CEOs, Vice Presidents, Directors and Managers, from large and small organisations, in both the private and public sectors across 60+ countries—and the community is growing (Palladium, 2019).

"Norton and I believed that measurement was as fundamental to managers as it was for scientists. If companies were to improve the management of their intangible assets, they had to integrate the measurement of intangible assets into their management systems". Focus is on creating 'value', not profit *per se* (e.g., customer value, employee value, shareholder value). Focus should not be on short-term gain, but on long-term success and value impact (Lepak and Smith, 2007).

An important element in BSC theory is the separation in leading indicators (also called performance measures) and lagging indicators (also referred to as outcome measures) for both financial and non-financial indicators (Kaplan and Norton 1996). This is not new; Granger pointed to the same separation (Granger, 1980)[5]. The main idea in BSC is to find relevant relationships (mostly by using correlations, but even better by defining a System Dynamic understanding of the dynamics in the system) between leading and lagging indicators (Kaplan and Norton, 1996).

According to Kaplan and Norton (1996), a fundamental tenet of BSC is that cause-and-effect relationships exist across measures within its four perspectives. Prior research on BSCs has provided equivocal findings as to whether these relationships exist. However, in a newly published article using data within the public sector finds evidence of causal relationships (Kober and Northcott, 2020).

Other challenges exist. The use of KPIs, for example, *how should we measure performance* (e.g., surveys, interviews, data from bookkeeping, etc.), and how often should we measure (e.g., daily, weekly, per hour, per month, per quarter), and how long a forecast period should we use? All this depends on what we want to accomplish. An example of a metric may be 'the number of monthly visitors' to a website, which is not a KPI unless the metric is part of the company's focus area. Other metrics that are relevant KPIs may be: EBIT (Earnings before interest and taxes), % of returning customers, or Market Share in % (see e.g., Bernard Marr KPI library[6]).

In the next three sub-sections, we will use the VNS framework to discuss the view and content of our course program. As shown in Figure 1, research involves the combination of some set of concepts, some set of methods for obtaining and comparing sets of observations, and some set of substantive events that are to be the focus of study. The process itself is the identification, selection, combination, and use of elements and relations from the conceptual, methodological, and substantive domains (Brinberg and McGrath, 1985).

1. The conceptual domain – 'performance measurement and management'

The conceptual domain (Brinberg and McGrath, 1985) involves and includes concepts and ideas in abstract form where KPIs and their relationships are properties in a performance model. KPIs are identified for each perspective where causal relations have to be established among these KPIs if we want to measure the effect on an outcome variable (Soderberg *et al.*, 2011).

Figure 4 shows how the strategy map links intangible assets and critical processes to the value proposition and customer and financial outcomes.

[5] Granger actually discusses three types of indictors in his book 'Forecasting in Business and Economics (1980, chap. 7.2); leading, coincident, and lagging, where a coincident indicator is an indicator that shows the current state of a metric. This metric should be used to give a full view of where the company has been and how it is expected to change in the future. How the three types of indicators interact depends on the formulation and the purpose of the model (Granger, 1980).
[6] See: https://www.bernardmarr.com/default.asp?contentID=773

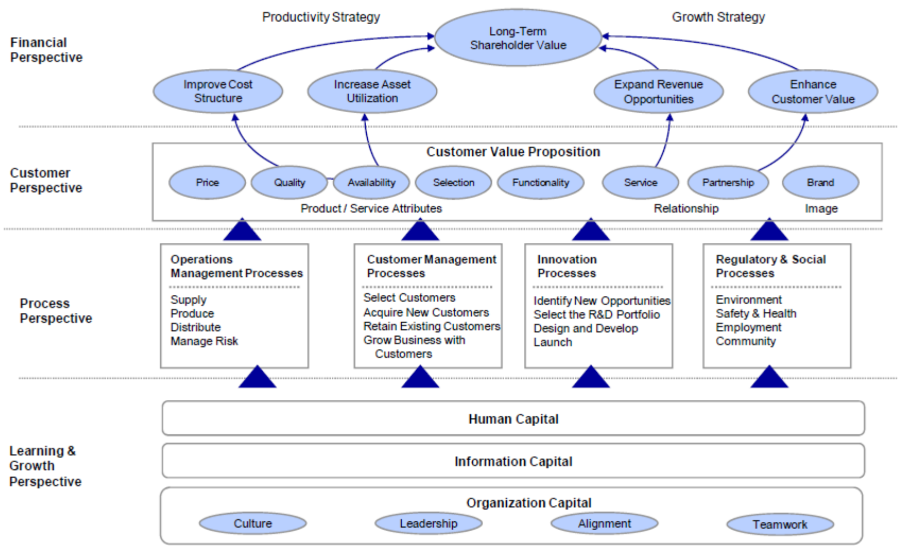

Figure 4: The strategy map links intangible assets and critical processes to the value proposition Ref.: Kaplan (2010)

The strategy map is part of the closed-loop system that combines the comprehensive framework suggested by Herb Simon (for score carding, attention-directing, and problem-solving) with the framework by Robert Anthony (for strategic planning, management control, and operational control). Rather than have them as separate activities, as suggested by Simon (1963) and Anthony (1965), we now have the entire range of activities for strategy development, planning, alignment, operational planning, operational control, and strategy control integrated within a comprehensive closed-loop management system (Kaplan, 2010).

A modern approach to PM&M is to design holistic PM&M models in combination with data analysis. A key concept is KPI. A KPI is a metric (it does not imply that any metric is a KPI). KPI stands for Key Performance Indicator. These three words define the specific function of a KPI[7]:

- **Indicator** means that it should show the measure or a number of something. For example, ‘How well are our customers engaged’ is not really an indicator; conversely, ‘Average customer engagement score according to the monthly survey’ is an indicator because it includes a score number.
- **Performance** means that it connects to a performance output– tangible or intangible. ‘The number of computers in an office per employee’ is a metric, but it may not be connected to the ultimate business performance that the company wants to measure. If you double the number of computers, you do not expect your profits to be increased.
- **Key** means that it should be important for your business and hence included as a topic in the strategy department.

In PM&M, KPIs are metrics that represent the strategy. Sometimes it is necessary to create new or proxy KPIs by using two or more metrics. In the case below, for instance, we have defined a new KPI ‘Average load factor’ by using two existing metrics, ‘Revenue Passenger Kilometer’ and ‘Available Seat Kilometer’. There exists a number of sites and places where the decision maker might get relevant data from, for example, Google Dataset Search, Google's Public Data Explorer, Awesome Public Datasets, Kaggle Datasets, US Census Data, or List of Machine Learning Datasets (Wikipedia). In addition, so-called synthetic may also be used. In a

[7] See also: https://bscdesigner.com/quantification-measure-metric-kpi.htm

general sense, synthetic data is information that is artificially generated, as opposed to collected from the real and business world. It is important to note that synthetic data is used for a variety of purposes for example for training of AI/ML.

However, neither the strategic map nor the closed-loop system give us any information about the strength of the associations between KPIs. If we think that we can safely assume constant lead/lag properties between the variables of interest such as KPIs and other important modelling variables, the correlation and linear regression theory presents itself as a very powerful tool in order to point out possible firm relationships. Tests such as the test for Granger Causality even seem to be able to give advice as to which is causing which, that is what is it that precedes what in a given relationship between two variables.

2. The methodology domain – 'techniques and software'

In the methodological domain, elements are modes of treatment of variables, that is, methods or techniques for designing model and gathering information and thereby adjusting a dataset (Brinberg and McGrath, 1985). The first important element is the different scales used in PM&M and how we can utilize these scales.

Search for relationships and patterns in datasets involving methods at the intersection of machine learning, statistics, and database systems (Hastie, 2009). There are many examples of using ML within different areas of performance, for example for the so-called 'customer churn problem' (see, e.g., Sabbeh, 2018).

An important assumption is to know about different scales. Normally, PM&M consists of several types of scales, as shown in the example below.

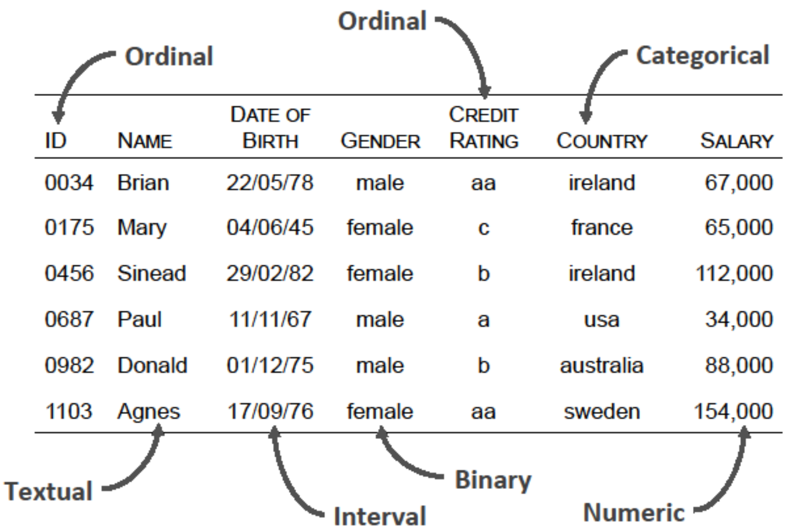
ID	Name	Date of Birth	Gender	Credit Rating	Country	Salary
0034	Brian	22/05/78	male	aa	ireland	67,000
0175	Mary	04/06/45	female	c	france	65,000
0456	Sinead	29/02/82	female	b	ireland	112,000
0687	Paul	11/11/67	male	a	usa	34,000
0982	Donald	01/12/75	male	b	australia	88,000
1103	Agnes	17/09/76	female	aa	sweden	154,000

Figure 5: An example of different scales for PM&M
Ref.: Kelleher *et al.*, (2015)

Using descriptive statistics (e.g., trends, a specific feature, or a certain statistic like a mean or median) and inferential statistics is important and may give a lot of information (see, e.g., Hill *et al.*, 2011; Kelleher *et al.*, 2015).

In our course, the methodology domain consists of using SAS Pro, @RISK 7.0 (for stochastic simulation and optimization) and Vensim for dynamic simulation[8]. Each of these software packages can be used for descriptive statistics, forecasts, prediction, prescriptive analytics, and for different types of 'training' an algorithm (part of machine learning). The advantage of using these software packages is that students can use the 'help' function, have access to a number of models and numerical examples and use the manuals for further inspiration and discussion.

To be able to evaluate the dynamic performance of a large number of possible control settings available to the management in a given company, it clearly requires a model of the company of some sort. It is often too risky to experiment with the company in real time. This is where the Balanced Scorecard conceptual model presents a starting point, with its four generic perspectives. Relevant KPIs have to be identified for each perspective, and causal relations have to be established among these KPIs. Now assume that we do have plenty of data recorded over time of the company's historic performance/outcome (KPIs). One way to deal with the elusive concept of causality is simply to theoretically assess possible directional relations between the available KPIs. Another way is just to start clustering KPIs in order to reduce the number of KPIs for each perspective and then correlating, in a lead/lag fashion, KPIs between the relevant perspectives in order to establish relations and possible causal indications. Causality between two variables means that a persistent relation exists between these variables (see, also, Kenny, 2004).

Does this mean that we should expect a constant correlation between these variables or even a fixed sign? Sadly, the answer is no, due to dynamic complexity that must be expected over time. This has primarily something to do with the lead/lag constellations. Three commonly accepted conditions must hold for a scientist to claim that *X* causes *Y:* (1) time precedence, (2) relationship, and (3) non-spuriousness. Omitting the third claim for the moment (but having it constantly in mind – it essentially covers the case where the correlation between two variables is high, but only due to the fact that they are both causally related to a common third variable), we can discuss a simple causal relation obeying (1) and (2). Let us consider $Y(t) = g(X(t-s(t)))$, where Y is causally influenced by *X*. Expressed like this the relation is not assumed to be linear, even if it is the most common assumption, and s(t) does not have to be constant, even if that is the most common assumption as well.

However, linearity and constant lead/lag $(s(t)=k)$ are necessary in order for the standard classic correlation measure to work, as it constitutes the computation of the correlation coefficient between the data *strings* $\{Y_T,Y_{T-1},...,Y_k\}$ *and* $\{X_{T-k},X_{T-k-1},...,X_0\}$. Clearly, if *'s(t)'* is not constant, we are not even able to put up the vectors to correlate.

There is an intricate relation between linear regression and the correlation measure Correl(X,Y) as the regression coefficient β relates to the correlation measure by the following formula: $b=Correl(X,Y)*(SY/SX)$ if $Y(t) = \alpha + \beta*X(t) + e(t)$, and *b* is the estimate of beta. Therefore, if we estimate the linear relation with X explaining Y, we can obtain estimates of α and β denoted *a* and *b*, respectively. We also get information about the residuals (hopefully mean zero and variance σ2). By using this relation $Y(t) = a + b*X(t) +$ 'residual noise effect', we are now able to infer the distributional properties of Y given distributional assumptions on X by the Monte-Carlo simulation method, X(t) -- f --> Y(t+s), where s is actually an unknown variable. Given certain stochastic findings regarding X (historically based), the future basic stochastic properties of Y can be forecasted. If s=0, the trick is to make the findings on X, future assumptions on X (also based on historical data, of course) and thereby predict the stochastic future of Y.

So returning to causal relations, either established by theoretical lead/lag arguments supported by various correlation measures or established by Granger Causal arguments, for instance, we seek relations of

[8]Other examples are e.g. Crystal-Ball (Oracle), BestFit (Decisioneering), or Analytical Solver Platform (Frontline Solvers). These simulation tools contain up to approximately 40 different and known probability distributions that can be used for input variables. Many distributions are of the PERT-type (Program Evaluation and Review Technique) also used in projects.

the type 'change in Y over period *t'* = $(Y(t+1) - Y(t)) = g(X(t-k), X(t-k-1), \ldots, t)$, expressing how the change in the variable Y comes about causally. This will eventually result in the next step Y value by the identity relation $Y(t+1) = Y(t) +$ *'change in Y over period t'*. This way to operationalize the concept of causality is exactly how it is done by the System Dynamics way of thinking, which makes this technique a relevant first choice when requiring a technique for computing the causal dynamically generated time paths for the variables at hand. LEVEL or Stock variables are system state variables, and their dynamic nature is then the result of simple mathematical integration, whereas the state change variables, the RATES, or the FLOW variables, are given/defined by specific functions, evaluating other state variables at given specific time lags. Because many state variables typically interact with different time lags, the resulting dynamic outcome can be quite complicated, even if the change functions are simple and linear by nature.

Both techniques, the risk Monte-Carlo setup and the System Dynamics time path analysis, reveal aspects of a complex future with respect to performance management. The first technique focuses on the possible future range of outcomes (max/min on a 95% confidence level) as a risk assessment for a given variable of interest. The second technique focuses on the possible 'complex time path outcome' given the starting assumptions for the system state variables and with the estimated change relations constituting the System Dynamics models anchored in the historic recent past. As such, the system computes the 'pure' time path into the future. If the future needs to be presented/analyzed in a more 'realistic' manner, the simulation into the future can, of course, also take into account the stochastic noise elements that have to be expected over time, extracted from the residuals obtained by the estimation operations in relation to the change relations. Distributional information relating to the risk aspect can be obtained in the SDM case, not only for some unspecified future time, but also for every future time instant.

Now assume that we do have plenty of data recorded over time of the company's historic performance. One way to deal with the elusive concept of causality is to theoretically access possible directional relations between the available KPIs. Another way is just to start clustering KPIs in order to reduce the number of KPIs for each perspective and then to correlate KPIs between the perspectives in order to establish relations and possible causal indication (see, also, Kenny, 2004).

3. The substantive domain – 'making data-driven decisions'

By combining concepts, and methods with focus on the empirical path, means that the students should be able to see a number of actual decisions that could be done called the substantive domain (Brinberg and McGrath, 1985). Making the 'right' business decisions has never been more consequential. Nevertheless, decision making also becomes more and more complex because more and more topics, IT and techniques are involved to reach a conclusion.

Clearly, the subject focus here is on the students learning process in the relation of how to base decisions on models, that are constructed in a data-driven fashion, and where the student is seen in the role as a decision maker. Looking into the definition of 'business analytics' this is defined as: *"the use of data, information technology, statistical analysis, quantitative methods, and mathematical or computer- based models to help managers gain improved insight about their operations, and make better, fact-based decisions"* (Davenport and Harris, 2007, p. 7). Decision makers need to have faith in their decisions and therefore the concepts combined with the methods used to support these decisions.

As Kim Warren (2004) put it *"However, like any profession, management requires that the tools they adopt will work, reliably, to solve the challenges that they face. Just as engineers expect the relationship between loads and stresses to be reliably understood, or doctors expect the link between obesity and hypertension to be well explained, executives need to be assured that they are working with good 'theory'— i.e. an explanation of which causes bring about what outcomes, and how that causality arises. Given such a* *sound explanation, they can intervene with the causal factors that are under their control, with confidence that the likely outcomes will more closely conform to their wishes"* (Warren, 2004, p. 333).

In our setup, this is achieved by putting emphasis on the conceptual supported lead/lag relations, obtained from the Balanced Scorecard thinking in combination with statistics and the causality understanding as conceptually put forward by System Dynamics. Experts differentiates between two types if decision: (1) decisions for which 'discoveries' need to be made within data (e.g., using exploratory analysis for customers), and (2) decisions that repeat, where decision-making can benefit from even small increases in decision-making accuracy based on data analysis (e.g., for banking and consumer credit industries in the 90s) (Provost and Fawcett, 2013). Fact based decisions or data-driven decision-making involves making decisions that are backed up by hard data rather than making decisions that are intuitive or based on observation alone. As business technology has advanced tremendously in recent years, data-driven decision-making has become a much more fundamental part of all sorts of industries, including important fields like medicine, transportation and equipment manufacturing.

A fundamental problem is overfitting of a dataset. If we look too hard at a set of data, we will find something—but it might not generalize beyond the data we are looking at. Data mining techniques can be very powerful, and the need to detect and avoid overfitting is one of the most important concepts to grasp when applying data mining to real problems (Provost and Fawcett, 2013).

For PM&M data-driven decisions involves collecting data based on measurable goals or KPIs, analysing patterns and facts from these insights, and utilizing them to develop strategies and activities that benefit the business in a number of areas. Fundamentally, it means working towards key business goals by analysed data rather than merely by shooting in the dark. However, to extract information and value from your data, it must be accurate as well as relevant to the goal. The earlier proposition 'garbage in garbage out' can in some cases be rephrase to 'garbage in, goodies out' meaning that using a few data cleaning techniques it becomes possible to clean up data more efficiently[9]. Figure 6 shows a number of concrete tips for better data driven decision making in order to find the best performance model. Actual this is an iterative process where the student continuously try to find the best model.

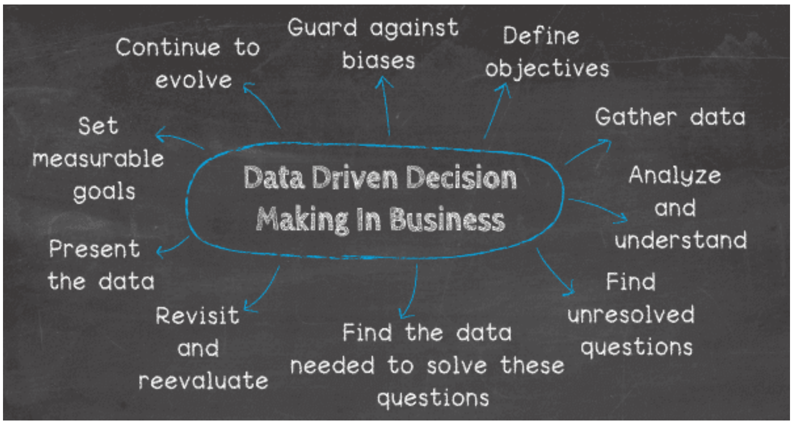

Figure 6: Practical issues in DDM
Ref.: Datapine blog: https://www.datapine.com/blog/data-driven-decision-making-in-businesses/

For example, if one wants to know how a given product might perform in a market, or how much net profit such a product might generate, different types of software can help. Because companies face such

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[9]There is a lot of discussion going on about what types of people and what skills are needed for the future. Companies need people that think like a 'scientist' - not necessarily a 'data scientist'. Scientists have to deal with every step of an experiment, from their conception to publishing the results. Learning how to use new tools or an algorithm is relatively easy and fast. Learning how to think of a business problem, on the other hand, is a slow and longstanding process (Granville, 2014).

situations every day (or maybe every hour), these types of decisions has led to a much bigger demand for data-driven decision-making solutions. Brynjolfsson *et al.* (2011) from MIT conducted a study of how data-driven-decisions affects firm performance. They developed a measure of data-driven-decisions that rates firms as to how strongly they use data to make decisions across the company. They demonstrate that statistically, the more data driven a firm is, the more productive it is—even controlling for a wide range of possible confounding factors. Besides, the differences are not small. One standard deviation higher on the data-driven-decisions scale is associated with a 4% – 6% increase in productivity. Data-driven-decisions also is correlated with higher return on assets, return on equity, asset utilization, and market value, and the relationship seems to be quite convincing.

In collaboration with SAS Research Report (2016) the MIT Sloan Management Review conducted a study to understand the challenges and opportunities associated with the use of business analytics and big data. In the report, the term 'analytics' refers to the use of data and related business insights developed through applied analytical disciplines (for example, statistical, contextual, quantitative, predictive, cognitive, and other models) to drive fact-based planning, decisions, execution, management, measurement, and learning[10]. The findings also show that despite the hype, the reality is that many companies still struggle to figure out how to use analytics to take advantage of their data:

> *It is hard work to understand what data a company has, to monitor the many processes necessary to make data sufficient (accurate, timely, complete, accessible, reliable, consistent, relevant, and detailed), and to improve managers' ability to use data. This unsexy side of analytics is where companies need to excel in order to maximize the value of their analytics initiatives, but it is also where many such efforts stall* (SAS Research Report, 2016. p. 3).

So returning to the teaching point of view, the following table explains how these considerations relating to the field of Data-Driven Modelling, in order to constitute a sound foundation for a Decision Support System, does split into several identifiable teaching/learning tasks, which techniques are required, and which objective is aimed for. Table 1 shows the basic issues we present for the students.

[10]The COVID-19 crisis has brought quantitative models to the forefront but also showed where to avoid its pitfalls (e.g., that a model is only as good as its underlying data or you are expecting too much certainty). Ideas associated with modeling, such as flattening the curve of disease transmission, are now regularly discussed in the media and among families and friends. We are all trying to understand the numbers and what they mean for us (see also, McKinsey & Company, 2020).

Learning Tasks	***Techniques***	***Objectives***
Learn how to select, visualize and reduce the number of KPIs in order to get a basic and preliminary idea of what data may be able to tell you.	Investigate if KPIs can be grouped into 'natural' groups corresponding to the perspectives of BSC, histograms, contour plots, and matrix scatter plots, as well as discussions of possible 'causality'.	Obtain a better understanding and a better way to use the KPIs and how this may help later on to separate different KPIs.
Learn how to find out if association between a strategy and specific predictors and KPIs exist.	Different types of regression analysis such as multiple regression, Lasso regression, Ridge regression, and correlations.	To be able to evaluate the prediction ability and to discuss assumptions and their effects from marginal changes for each predictor.
Learn how to combine predictive analytics with prescriptive analytics, in order to perform specific optimization scenarios for PM&M.	Monte Carlo simulation, optimization and stress analysis including a number of constraints for specific KPIs. The results are presented as progress graphs over the number of trials and as a summary report including the values of the relevant KPIs.	To be able to evaluate and discuss the numbers and implications of the complete outcome.
Learn how to differentiate between Stock (Level) and Flow (Rates) variables (because any explanation of Stock variables apart from integration is seriously problematic).	Investigation of units of measurement. Stock (Level) variables are measured in UNITS, whereas Flow (Rates) variables are measured in UNITS/'Time Unit of measurement'.	Obtain an increased level of understanding, in going from a CLD understanding to a more complete SFD understanding.
Learn how to identify relationship between variables for possible causal relationships.	For a causal relation to exist in a true dynamic sense the explaining variable has to lead the explained variable in time. This is studied by use of Cross-correlograms.	Obtain a more specific insight in the possible lead/lag relations between variables of interest, for later use.
Learn how to estimate (linear as well as non-linear) relations, where stock variables are used to explain a given Rate variable. The basic SD logic is never to explain a Stock (Level) variable by anything else as by integration.	The important part here is to search for statistical significant coefficients and not so much for a good fit. It is not the regression model that is going to perform the 'forecasting' task, but the full dynamic SD model.	Obtain knowledge in general and obtain good approximate quantifications in specific in relation to the systems behavioral part.
Learn how to run a full dynamic system analysis with respect to establishing a model that performs reasonably well on historic data, in extreme test situations as well as shows sound long-run stability behavior	Computing the models behavior both by numerical experiments (scenario simulations for example in VENSIM or Excel) as well as by algebraic solution of the long-run dynamic equilibrium conditions if possible.	Obtain extended knowledge about the dynamic systems full potential of complexity, handled so far. Get a good grip on the degree of approximation we are dealing with so far.
Learn how to introduce noise in the scenario runs of the SD model, typically based on the estimated noise levels from the regressions used to construct the models behavior-relations, in order to perform specific risk-evaluations for given variables at given time instances.	Repetitive simulation runs based on repetitive draws of random numbers relating to specific random variates. The results are typically presented in histograms, where the result variables various probability outcomes can be studied.	Obtain model context based decisions, where uncertainty is taken into account.

Table 1: Example of topics with its teaching tasks, techniques and objective.

The basic purpose of 'data driven decisions' is – to create both value and impact in the company. Experience has, however, shown that this is hard work and assumes in fact the presence of a lot of talent and skills in order to be able to fulfil these outcomes (Davenport and Harris, 2007; Silvestro, 2014). At the operational level, this is often easier than at the strategic level (Fact based decisions; Tableau, 2012: 'Decisions follow facts'). Strategic decision making tends to be very different and much more complicated: too many variables (e.g. markets, customers, products, and processes), too little structure, and too much uncertainty (Simchi-Levy, 2014). As such, the education of young people seem a most urgent job for the universities and in this light, our endeavour seem quite relevant.

C. Using a case company for learning

Below we will discuss some issues of our learning objectives used in two workshops. We use data from the airline industry, because the airline industry is probably one of the most analyzed and discussed industries (together with railroad industry). There exist a lot of information, both qualitative information and quantitative (see, e.g., Wu and Liao, 2014 and the references) public available (see e.g., IATA Consulting, 2017; ICAO, 2009 etc.). Often concepts such as 'Airline Analytics' is used to emphasize the importance of performance and the value of data within the industry.

Specifically, we use data from Financial Interim Reports data for the SAS-Airline Company from 2009(Q1) to 2019(Q2). We have augmented these data with other relevant data for performance. Even though the actually needed PM&M data (internal of nature) are somewhat different from the information given to the public (external of nature) there seems to be a trend toward more internal information also given to stakeholders (see e.g., Joshi, 2018 and Gupta *et al.*, 2016)[11]. Several Airlines, for example Southwest Airlines[12] also use the BSC model.

The available data is explored for possible relations:

- To be able to explore data in order to discover new relationships and patterns.
- To move from observations and data in unstructured form (raw observations) to a more structured form. We align and correct the data to the same periodicity, most likely explored by cross-correlogram investigations.
- To transform the data-driven knowledge obtained so far into a model setup, which can form the basis for potential decision making for normative decisions.
- To be able to explain why certain results occur, their generality or specificity given the statistical nature or dynamic system complexity.
- To be able to evaluate previous and alternative decisions in order to predict future trends (predictive modeling).

To summarize, the focal aim of the course is to let the student experience the full process of going from data → model → performance → decisions, using the tools obtained in previous courses and the specific tools learned in the present course such as Monte Carlo simulations/optimizations and System Dynamics.

The learning objectives seem to be well aligned with our teaching ideas why we put a lot of effort into hands-on activities. Such activities are supported by the use of PCs and the selected software used. This creates an environment of 'active learning', where students form groups discussing model design and evaluate the outcome (Dhanapal and Shan, 2014; Henning *et al.*, 2019). In fact, it seems that we do what Henning *et al.* (2019) call 'Small Teaching', meaning that we are in the classroom with the students throughout the semester course (there are about 40 students enrolled in the course) and we are responsible for all help and sparring to the student-groups as needed.

We have developed and improved our syllabus during the five course-runs conducted so far. Two important questions that we have constantly asked ourselves *"why is this subject important now?'* and '*is this a good way to teach this subject?"* (CABS, 2019; Srinivasan, 2019[13]).

The hands-on learning approach engages the students actively in learning (Ekwueme *et al.*, 2015; Haury and Rillero, 1994). The advantages are simply that by doing hands-on activities, the students seem to remember much better and in addition to that, they seem to feel a sense of accomplishment when the hands-on exercises are completed. These benefits are achieved because the information has a better chance of being stored in the brain of the student for useful retrieval (Dhanapal and Shan, 2014). Our idea is to move away from the traditional lecture-heavy format and to facilitate learning as a 'mentor in the center' instead. We

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[11]The traditional data warehouse still serves as the basis for analytics programs and remains foundational. However, increased demand for new data types and new use cases continues to expand. Data warehouse architecture has to evolve in order to meet these demands in both distributed and centralized solutions (Gartner, 2017).

[12]See https://www.destinyjackson.org/blogs/articles-essays/balanced-scorecard-southwest-airlines

[13]See: https://hbsp.harvard.edu/5-steps-to-designing-a-syllabus-that-promotes-recall-and-application/?cid=Email%7CEloqua%7CNewsletter+1+Aug+2019%7C55019%7CProduct+specific%7CNewsletter%7CEditorial-Article%7C201908271499

have activated the students by making a number of suggestions they can discuss, for example the quality of the data and the definition of the KPIs.

In general, we have mimicked real-life situations that graduates eventually will experience in practice (Bonwell and Eison, 1991).

During the course, we keep discussing these points with the students through a number exercises (Appendix A shows the total lecture plan for the course) referring to the figure by Davenport and Harris (2017) (see fig. 1).

An example within PM&M may illustrate the differences between past and present way of teaching:

> *For a performance management system such as the balanced scorecard, we teach how many KPIs a company could or should use, how to define the KPIs, the relation to different perspectives, and why and how the KPI should be related to the firm's strategy. However, normally, we do not teach for example, the sensitivity or changes in causality from the customer perspective to the financial perspective, nor which KPIs will have the greatest affect our future growth and profitability, or when can we expect our present strategy to peak under the present circumstances. Therefore, we cannot demonstrate the use and the effect this has on our decision making process on short or long run or on the financial perspective (e.g., by using different time-lags situations) or which KPI is the most important ones for our financial outcome under different scenarios. Therefore, the students will never experience the interaction between data, model and decision using different types of available KPIs, or the effect of different ranges of uncertainty in a performance model.*

It is not enough only to discuss WHAT and HOW, we have to include the WHY that is of great importance for the decision-maker under BA (Davenport and Harris, 2007; Davenport and Kim, 2013; Blocher, 2009; Ferreria and Otley, 2009). LaValle *et al.* also support this (2010, p. 1) by saying: *"Knowing what happened and why it happened is no longer adequate. Organizations need to know what is happening now, what is likely to happen next and what actions should be taken to get the optimal results"*.

In stream B (see, Appendix A), the students acquire a deep understanding of how correlations of all kinds (cross and auto) can support the search for causality. The type of causality in the present context is the type of causality intrinsic in the System Dynamics way of thinking about causality. Without getting too philosophical, causality in System Dynamics is understood by a rule that RATE-variables are the driving forces, and LEVELs are the result of a simple integration over time. This is in line with the 'Newtonian' concept of causality that requires a force that results in either an acceleration or a speed that leads to a system state change and becomes the result of simple integration over time of certain differential equations. Essentially, one may say that the System Dynamics understanding of causality is inherently Newtonian by nature.

We have mapped the arc of the PM&M course into the following themes, techniques, and outcomes shown in table 2.

Theme	*Technique*	*Learning outcome*
Intro to BSC as a Closed Loop Management Analytical System, business analytics	Defining variables (different scales), correlation vs. cause and effect on output, proxies	To be able to identify and describe how the BSC framework can be used – but also explain its limitations
Defining and mapping KPIs, their relationships, and their scales	Multiple regression, causal model and predictive models	Interpretation of output reports
Building a BSC model, strategy and selection of the most important KPIs	Cluster analysis, discriminant analysis, and factor analysis (data mining)	Reporting on differences between causal models and prediction models
Introduction to the uncertainty of KPIs and the effect on outcome using ABC (Activity-Based Costing)	@Risk simulation	The meaning of input uncertainty for outcome, skewness, kurtosis, and reducing standard deviation
Fitting distribution based on data; the relevance of the Beta distribution	@Risk fitting tool	The importance of different probability distributions of outcome
Optimization of a PM&M	@Risk optimization	Be able to reach the advanced level of BA
Mapping of more or less strong correlation patterns indicating possible Lead/Lag relations	Cross-Correlations (CC) (Search for Lead/Lag structure)	That correlations are definitely not equal to causality, and correlations are estimates that should always be accompanied by confidence limits
Critical rational discussion of possible causal structure	Closed Loop Diagramming (CLD) and Stock Flow Diagramming (SFD)	That CLD/SFD is a useful technique in establishing a common understanding of a given BSC setup.
Empirical support for a possible Granger-causality between the variables at hand	Granger Causality to support (CC+CLD analysis)	The importance of predictive power when discussing causality
Empirical determination of various behavioural or table-like relations in a System Dynamics Model. Determination of Flow(Rate) expressions	Multiple regression combined with the System Dynamics logic (only Rates and Auxiliary variables can potentially be explained by regression)	That in principle all level variables (also denoted Stock variables) are the result of elementary basic integration, and hence it is pointless to determine such variables in any less precise manner
Time Series (dt=1) simulation of a System Dynamics Model based on the causal thinking embedded in the System Dynamics logic	Simulation by Integration, that is simulation of a system of difference (differential) equations (VENSIM)	Validation of the dynamic model by performing historical data runs, extreme parameter value runs, test for dynamic stability in the long run, risk-based performance assessment and analysis
Easy transformation of a System Dynamics Model to an Excel model in case dt=1	Correspondence between VENSIM and Excel formulations of a given dynamic model	Pro and cons from using VENSIM/Excel, respectively

Table 2: Themes, techniques, and learning outcomes for the two streams

Students are urged to come up with a simple strategy to test such as for example, '*we want to improve profitability for customer group A*' (for example because profit has declined over the last quarters) or *'we want to investigate the reasons why a specific group of costs have increased and how it can be reduced'*. For that purpose, they may use data analysis and data visualization techniques as proposed for data-driven modelling (e.g., Alteryx, 2017; Janvrin *et al.*, 2014; Davenport *et al.*, 2010). Students have numerous techniques to choose from such as path analysis (Perlman, 2013) or simple visualization relationships between features or variables (Kelleher *et al.*, 2015) or SEM (Duncan, 1966; Hair *et al.*, (1998)[14].

Several authors have discussed which KPIs are the most important KPIs for airline customers. Examples are; (1) Security: wait time; (2) Check-in: wait time; (3) Baggage: Mishandled baggage; (4) Flights: gate allocations, on-time performance; (5) Immigration: wait time; and (6) Baggage reclaim. Other relevant KPIs are RPK (Revenue Passenger Kilometers) and ASK, (Available Seat Kilometers), Average Load Factor, Unit cost, and Yield (Demydyuk, 2011). Finally, the student may find sites where further airline information can be found[15]. Because the dataset we use includes data over time (time-series data), students must control and adjust for stationarity (Makridakis et al, 1998)[16]. A distinguishing feature of time-series

[14]See for example Perlman (2013), where path analysis is used for different types of project and their benefit.
[15]For safety: https://www.asms-pro.com/Modules/SafetyAssurance/ListofAirlineKeyPerformanceIndicators.aspx
Market indicators: https://marketrealist.com/2014/09/must-know-key-indicators-impacting-airline-industry-performance
Consideration of KPIs: https://www.quora.com/What-all-are-the-KPIs-that-we-can-consider-for-the-aviation-airline-industry
KPI-Library: http://kpilibrary.com/categories/airline
ReportLinker: https://www.reportlinker.com/
Business analytics: https://www.targit.com/en/blog/2017/09/best-airport-kpis
[16]In Stream A, we only use techniques related to cross-section data.

data is its natural ordering according to time. With cross-section data there is no particular ordering of the observations that is better or more natural than other orderings (Griffiths *et al.*, 2011).

An important issue in PM&M is the discussion of lags for KPIs (see also Kaplan and Atkinson, 2014; Kaplan, 2010; Kaplan and Norton, 1996). Therefore, the students are encouraged to investigate lag structures and their influence. We also discuss the important topic of whether 'to explain or to predict' (as said by Shmueli and Koppius, 2011).

Figure 7 shows the output from the simulation using the dataset for SAS-Airlines (after adjusting for serial correlation) together with a 'Tornado graph' based on ranked output.

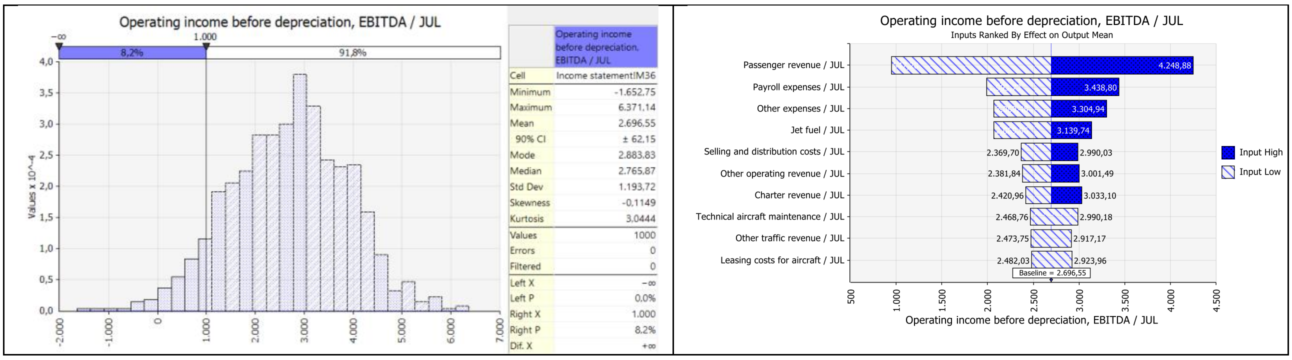

Figure 7: Different probabilities and their relationships

As we can see that, there is a probability of 8.2% to get a result below $1 billion and some further information about the forecast variable that is normally not available in a deterministic approach. The students discuss this type of information and come up with ideas for improvement for the future.

Now we turn towards the hunt for a causal and explicit dynamic understanding of the reasons behind the observed Airline data (main topic of stream B). A few variables immediately attract our attention.

One reason is the general understanding that demand and supply are basic variables in any economic description of a given situation. In addition, the BSC way of thinking views the customer perspective and the internal process perspective as fundamental and interacting elements when setting up the actual driving part of the BSC that eventually feeds the financial perspective and again influences the real economy. The variable 'RPK' belongs to the customer perspective and the variable 'ASK' belongs to the internal process perspective. The connecting variable is 'ALF' as it can act both as a KPI for the customer satisfaction as well as the utilization of the producing capacity (can be found in Appendix B).

The sequence of the teaching activities in stream B across the semester can equally well be illustrated in the flow-charts illustrating the sequence of activities in the two workshops, workshops I and II, relative to the stream B activities, which are listed in table 1 above. The theory relating to stages 1, 2, and 3 are, of course, the main topics before executing the first workshop (Workshop I)

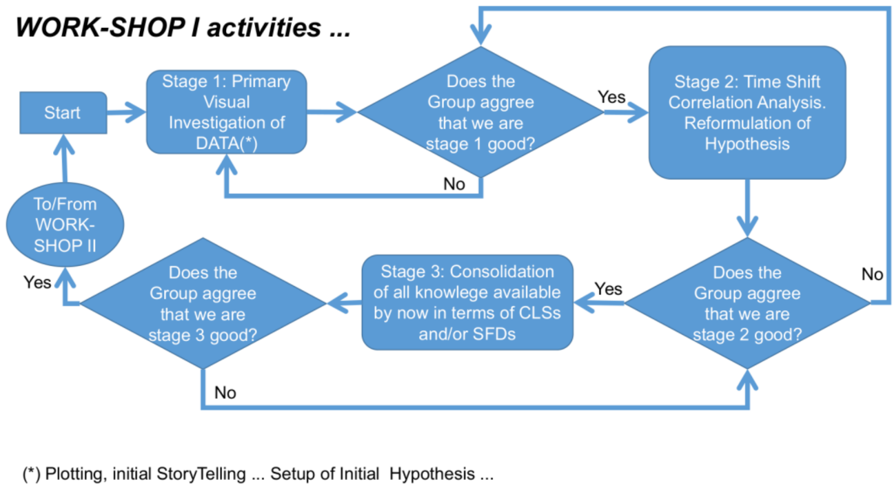

Figure 8: Flowchart illustrating the flow of activities in the workshop/course

The theory relating to stages 4, 5 and 6 are then the main topics before executing the second workshop that is the finishing activity of the course (Workshop II).

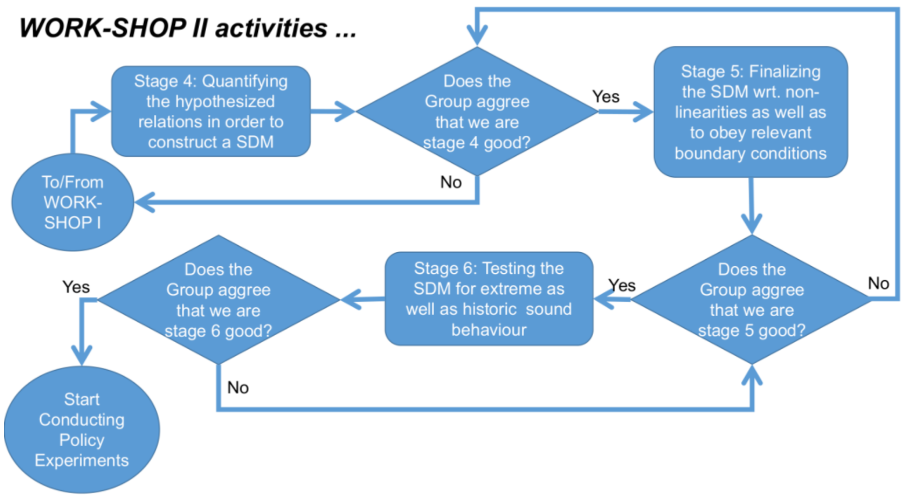

Figure 9: Flowchart illustrating the flow of activities in the workshop/course

The pinnacle of the stream B activities is then a fully specified core model and the utilization of such a validated model. We are clearly not pretending to be able to run real policy performance evaluations, but the model has been constructed based on data-driven principles. The System Dynamics model relations (the Rates) have been constructed as sound and significant regression relations and the necessary non-negativity conditions are observed for the relevant variables (RPK>0, ASK>0 and ASK>RPK). The only back-draw so far is that it is a version 1.0 model and given some more time and effort such a model can, of course, be improved. Anyway, this version 1.0 model can be used to illustrate the potential for policy analysis and to illustrate the power of such a System Dynamics model with respect to the evaluation of specific policies.

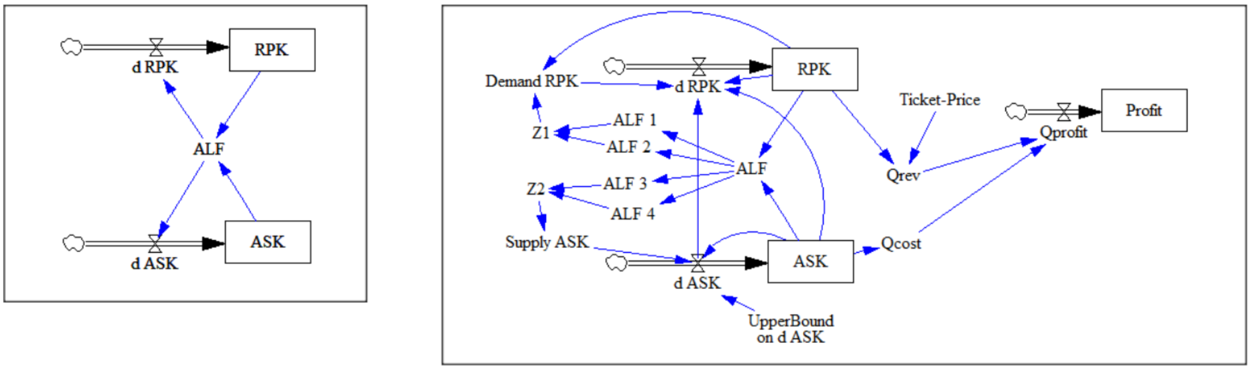

Figure 10: The core model

Given some further parametrization of the model (cost coefficient and price) where the base run shows an unfortunate long-run development in the profit (accumulated profit) going into the negative. The ALF-plot (left) shows a tendency towards low utilization too much of the time, and the policy that comes into mind is to put a limit on the increase in the number of seats in response to a decrease in the number of customers (trying to increase the comfort and thereby increase the customer satisfaction). Dampening the ASK response results in an average load factor value (ALF to the right) that is significantly higher over time, and an accumulated profit that returns to positive as time goes by.

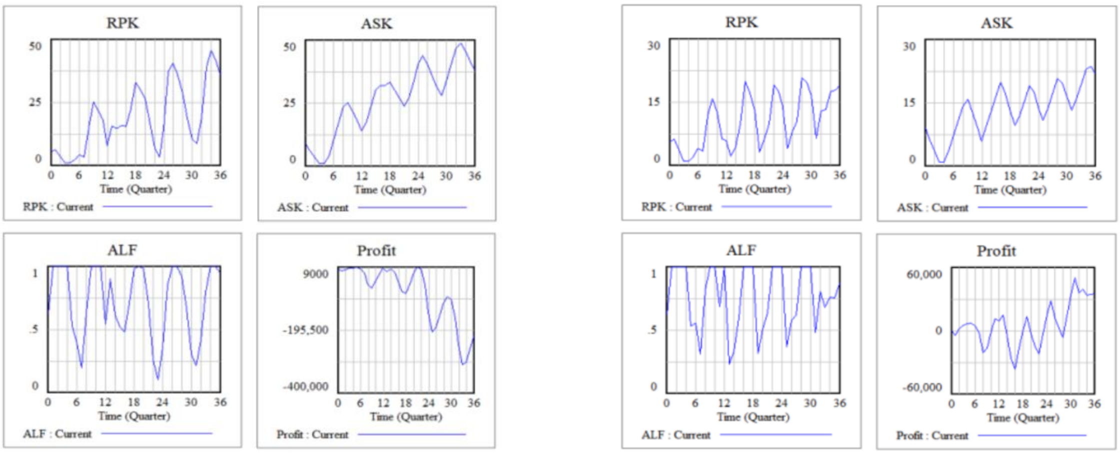

Figure 11: Results from a base run (left) and a run based on a policy where dASK is limited in its ability to take positive values (right)

The learning that we hope to give the student is that it might be worthwhile to study data, build a model, validate, refine the model and to increase the degree of detail step-wise until the model fits the needs. Data talks, models informs and decision makers (giver det mening Karin?) can finally engage in dialectical conversation with the dynamic complexity of real life. That is what analytics is also about. Practical business analytics.

Figure 12 shows an example of the partitioning (splitting) of our SAS Airlines dataset based on 'Revenue passenger Kilometer (RPK or Airline Demand)', 'Available Seat Kilometer (ASK or Airline Supply)', and 'On-time departure in %' as these are some of the most important KPIs for the airline industry (Demydyuk, 2011). The technique of data partitioning is often considered as a data mining technique because it is useful for exploring relationships in the absence of a good prior model (Dean, 2014). A classic application of partitioning in performance is to create a diagnostic heuristic for customers. Given symptoms and outcomes for a number of customers, partitioning will generate a hierarchy of questions to help diagnose problems for customers for example. Because our data set only contains 43 observations, the students are encouraged to follow a bootstrapping procedure. This also helps in order to get both a validation set, a test set (also called a holdout set), and a training set, which will come in handy later on in relation to further discussions of the students.

When the response variable is categorical (like in our case), then the fitted value is the probability for each of the levels of the response variable. The split function in SAS Pro maximizes the difference in the responses between the two nodes of the split. As seen from the top of the figure 12, the first information meeting us is the number of observations between the tree datasets. The nest is the final R^2 value for the validation set that lies between 0.54 and 0.58 (it estimates the proportion of variation in the response that can be attributed to the model rather than to random error). The decision tree below shows the tree splits and the counts of observations in each split.

The vertical axis to the left in the figure is the proportion of each response outcome, divided into levels of the response variable and to the right the name and the order in which the response levels are plotted (0 to 20% Bad; 21% to 40% Acceptable; 41% to 50% Moderate; 51% to 70% Good; and 71% to 100%; Excellent).

The vertical lines extend into the plot and indicate the boundaries for each node. The most recent split appears directly below the horizontal axis and on top of existing splits.

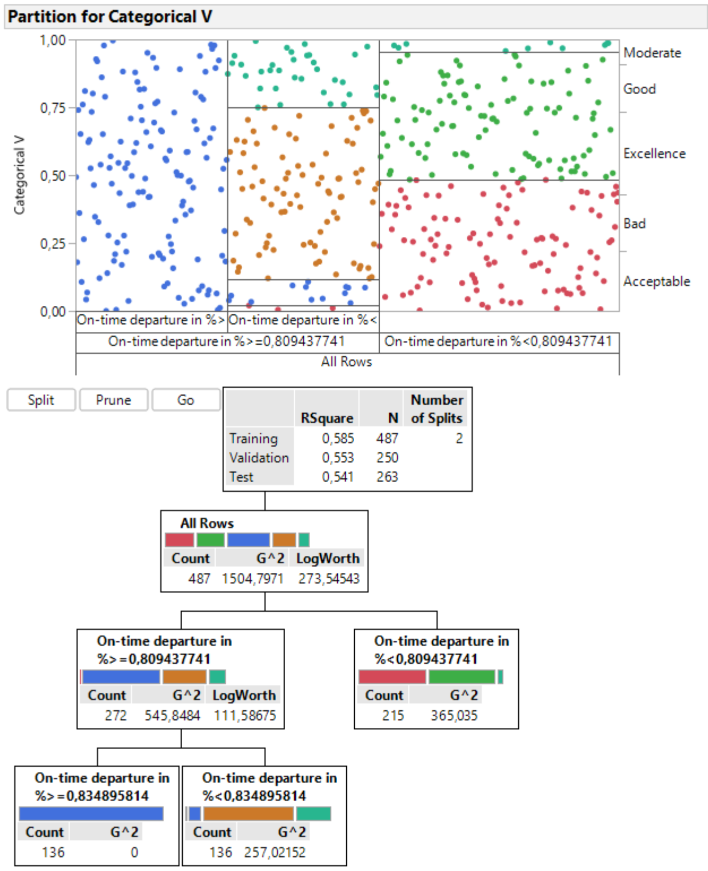

Figure 12: Partition on revenue and two KPIs

According to the SAS Pro manual (SAS Institute, 2018), the partition algorithm searches all possible splits of predictors to best predict the response. These splits (or partitions) of the data are made recursively to form a tree of decision rules. The splits continue until the desired fit is reached (here we only show tree splits). The partition algorithm chooses optimum splits from a large number of possible splits, making it a powerful modeling and data discovery tool. Each point in the Partition Plot represents one observation in the data table[17].

The first split shows that 'On-time departure in %' is dependent on whether the value is below or above 0.80. The second split on the left hand side depends on whether the value is below or above 0.83. We can also see that even though we use two other predictors (RPK or Airline demands and ASK or Airline supply) – the software only splits on the 'On time departure in %', because this is apparently the most important one.

Finally, we want the students to try out a simple prediction algorithm, in which performance is measured by the ROC[18] measure – in order to inspire them to immerse themselves in the subject. We have chosen the Naive Bayes classifier algorithm, as this is one of the most simple but surprisingly powerful algorithm for classification and predictive modeling (Brownlee, 2019).

The training set estimates the model parameters, the validation set is used to help choose a model with good predictive ability, and the testing set checks the model's predictive ability after a model has been chosen. There are no fixed recommendations on the size of the different datasets when holdout sampling is used, although training: validation: test splits of 50:20:30 or 40:20:40 are common (Kelleher *et al.*, 2015). This gives the decision maker (in our case the student) more exact information about the prediction ability for these levels (below we only show output from acceptable and excellent levels) where the student can try out different percentages for the three splitting levels.

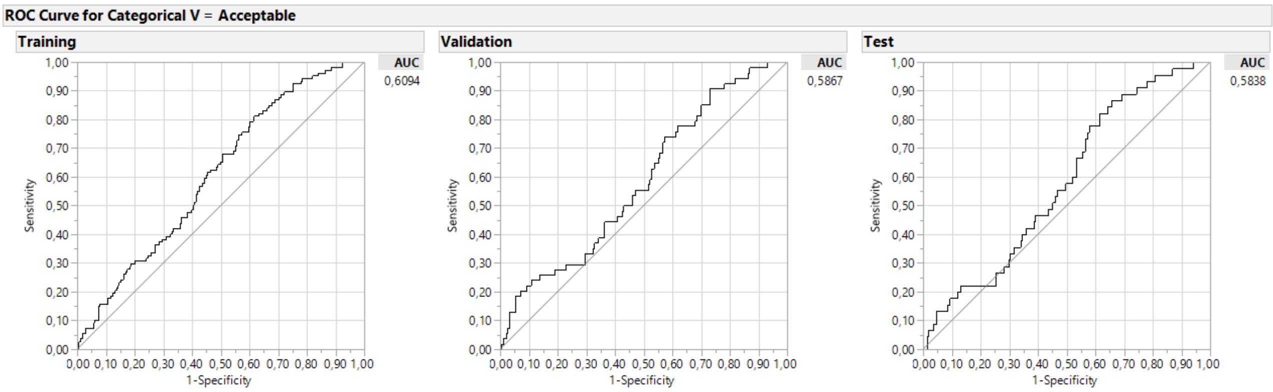

Figure 13: The ROC curve for level 'acceptable'

Using the output from SAS Pro the students can display the Receiver Operating Characteristic (ROC) curve for the Training set and for the Validation and the Test sets[19]. The ROC curve measures the ability of the fitted probabilities to classify response levels correctly. The further the curve is from the diagonal, the better the fit (Brownlee, 2019). If a test predicted perfectly, it would have a value above which the entire abnormal population would fall and below which all normal values would fall. It would be perfectly sensitive and then pass through the point (0.1) on the grid. The closer the ROC curve comes to this ideal point, the

[17] Because we use validation, SAS Pro can only give us the plot for the training data. The initial partition plot does not show splits.
[18] A **receiver operating characteristic curve**, or **ROC curve**, is a graphical plot that illustrates the diagnostic ability of a binary classifier system as its discrimination threshold is varied.
[19] Using SAS Pro JMP students must define a 'validation' variable and define the Y-variable as a categorical variable. The ROC curve is only available for nominal or ordinal responses.

better its discriminating ability. A test with no predictive ability produces a curve that follows the diagonal of the grid (DeLong *et al.*, 1988).

The area below the curve is the indicator of the goodness of fit for the model. For example, a value of 1 indicates a perfect fit and a value near 0.5 indicates that the model cannot discriminate among groups.

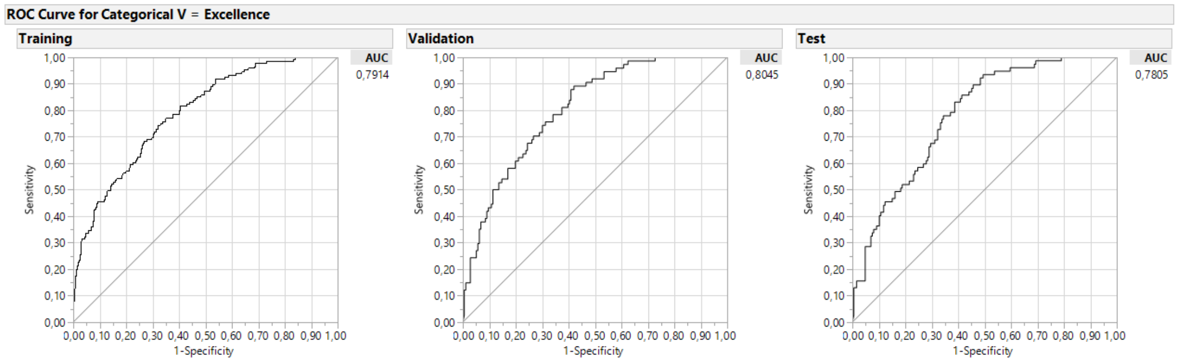

Figure 14: The ROC curve for level 'excellence'

The ROC curve in figure 15 is well above a diagonal line, and hence the student may conclude that the model for 'excellence' has a good predictive ability, which is better than the predictive ability for the level of 'acceptable'.

D. Student assessment

This section summarizes survey data from students who completed the course during the autumn 2018 and 2019 semesters. In addition to designing and teaching a relevant course, our goal was to evaluate the outcome from hands-on and different types of software used for the course. To this end, we conducted a survey based on 48 students (out of 78 students over two years) to be able to get more information about how the students think and behave. Therefore, we did two types of statistics: some descriptive statistics and a SEM (Structural Equation Model) to be able to see the relationships between different batteries of questions in the questionnaire.

1. Descriptive statistics

In the development of the survey instrument, we used earlier research on different types of teaching performance measurement. Given the specific aim of our study, we also decided to develop instruments ourselves to assess the outcome of teaching DDD performance measurement and management.

Questions are inspired by a number of teaching research articles such as: 'Teaching simulation in general' (Boyce, 1999; Riley et al, 2013), 'teaching data-driven decision making' (Ballou *et al.*, 2018), 'Teaching spreadsheet modelling (Borthick *et al.*, 2017; Frownfelter- Lohrke, 2017); 'Using @Risk' (Schriber, 2009; Togo, 2004), and 'Teaching System Dynamics' (Bianchi, 2016; Cosenz and Noto, 2015; Warren, 2004)[20].

A survey based on self-perceived answers to 15 questions was distributed to the students at the end of the course. We used a five-point Likert-type scale (1 = ''strongly disagree', . . .,5 = 'strongly agree'). Table 3 shows the survey questions, response frequencies, together with mean and standard deviation for each question. The questionnaire consists of five groups of questions (or latent variables); first group (1. Que, 2.

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[20]There is a large number of articles related to teaching different technologies and subjects, for example 'simulation'. However, the idea here is to use articles that also include an evaluation aspect from the students of these different teaching issues and tools. For gamification and simulation in education and corporate Learning, see e.g., https://inoxoft.com/gamification-and-simulation-in-education-and-corporate-learning/

Que) consists of background or contextual questions; second group (3. Que, 4. Que, 5. Que, 6. Que) consists of questions related to input exercises; third group (7. Que, 8. Que) is related to the use of @Risk software, fourth group (9. Que, 10. Que, 11. Que, 12. Que) consists of questions related to CLD (Closed Loop Diagrams) and SDM (System Dynamics Modeling), and the fifth group (13. Que, 14. Que, 15. Que) includes questions related to students' evaluation of the course. The idea was to balance the number of questions and the validity of answers and to compare these elements with the aim and purpose of the course. One thing is what the teacher thinks; another thing is the actual outcome seen from the perspective of the students. The course consists of many different topics, datasets and types of decisions. For the number of topics to be taught effectively, students need to be familiar with different statistical tools as already mentioned. However, both @Risk (7. Que and 8. Que) and the Vensim software (13. Que, 14. Que, 15. Que) are new to the students, whereas the majority of the statistical techniques are already known from earlier courses. Inspiration for selecting questions on business analytics and data decisions can be found in Everaert *et al.* (2007), Mardikyan and Badur (2011) and in Wynder (2010). To make the students understand the relevance of the course, we included several small cases illustrating many different problems and aspects of data driven decisions.

We used closed questions with known words relating to the specific topics, which should increase the validity (Burgess, 2001; Dillman, 1991). Table 3 summarizes the survey results for 48 students.

Question items	***Strongly Disag. (1)***	***Disagree (2)***	***Unsure (3)***	***Agree (4)***	***Strongly Agr. (5)***	***Mean***	***Std Dev***
1.Que: I have a good knowledge of traditional PM through my earlier courses	1	12	14	16	5	3.08	0.114
2. Que: BA in relation to PM is an interesting subject	1	1	9	27	10	3.85	0.123
3. Que: Exercises during the course have improved my general understanding of data-driven decisions	0	2	8	21	17	3.91	0.123
4. Que: Hands-on exercises during the course have improved my general understanding of Performance Measurement	0	1	9	27	11	3.97	0.126
5. Que: Hands-on exercises during the course have improved my understanding of using statistics through SAS Pro JMP for PM	1	7	13	18	9	3.83	0.126
6. Que: Exercises have improved my understanding of the connection between KPIs	0	0	10	21	17	4.10	0.139
7.Que: @Risk Monte Carlo simulation has increased my understanding of building and using different models	1	3	15	19	10	3.68	0.153
8. Que: @Risk optimization has increased my understanding of building and using different models	0	4	12	21	11	3.70	0.123
9. Que: CLD/SDM methodology has given me a better understanding of the concept of 'causality'	0	7	6	22	13	3.91	0.119
10. Que: CLD/SDM methodology has given me a better understanding of the way a linear regression can be used in more complex relationships	4	7	11	20	6	3.35	0.115
11. Que: CLD/SDM methodology has given me a better understanding of how a dynamic performance model can be used for more basic structure elements	0	8	15	18	7	3.33	0.103
12. Que: The CLD/SDM methodology has given me a better understanding of ways to link data to a model	0	4	7	23	14	3.85	0.110
13. Que: Exercises generally have increased my engagement in the different scientific issues	1	7	12	17	11	3.70	0.114
14. Que: Hands-on exercises in general are specifically relevant for this course	1	1	6	22	18	4.14	0.123
15. Que: Workshops with hands-on in total have been good for a deeper understanding of the scientific issues	0	4	5	25	14	4.08	0.123

Table 3: Results from the questionnaire for mean and standard deviation

In general the results demonstrate that students thought the course provided a good or better understanding of PM&M using the included tools (by using words such as 'improve', 'increase' in the questions) than would otherwise have been the case (for all questions, mean is above the average of 3.00). Students also thought hands-on increases their general understanding of performance management and statistics (4. Que) appropriateness of a traditional view (mean = 3.97), and improves their understanding (5. Que) of using statistics, in this case SAS Pro (mean = 3.83). Specifically, it seems important to use exercises (6. Que) when it comes to discussing different KPIs and their relationships (mean = 4.10). However, in terms of building different PM&M models using the @Risk software (7. Que and 8. Que), the students find that @Risk improved their understanding (mean = 3.68 and 3.70). @Risk seems to be very user friendly (see, e.g., Albright and Winston, 2017 and Schriber, 2007) for students in Operation Management and BA - and an interesting and relevant software package for building prescriptive analytics models.

When it comes to system dynamics (9. Que and 10. Que), these two questions get high scores (mean = 3.91 and 3.85). Because the students have not had any experience with this topic earlier in their study, and because system dynamics may also be a difficult technique to use, we are surprised to see that the scores are so high. However, we did several simple examples using CDL explaining the 'stock' and 'flows' concepts using only a few KPIs. More advanced topics (e.g., formulation of differential equations) were not part of this course. Emphasis was also put on how to move from Excel to SDM and vice versa, which is an important exercise. SDM is undoubtedly one of the most relevant and advanced tools for dynamic performance (Barnabè and Busco, 2012; Kaplan & Norton, 2008; Warren, 2004). We choose to let the evaluation of scientific exercises (mean = 3.70), the evaluation of hands-on exercises (mean = 4.14), and the evaluation of two workshops (mean = 4.08) represent our response variables. Comparing to other similar studies, this study has a more exploratory character based on several data-driven decision topics including both different cases and different stand-alone datasets (see Appendices A and B). Finally, it is important to remember that the course is an elective course - meaning that only students who have an interest in these topics are going to participate.

2. Structural equation modelling

Structural equation modeling is often used in evaluating student attitude or outcome from using different concepts for different types of assumptions where a number of input variables may be related (e.g., Berger and Boritz, 2012), or when the idea is to evaluate the use of educational computer programs to enhance student performance (e.g., Chan *et al.*, 2016). PLS overcomes many of the theoretical and estimation problems that are normally related to the use of covariance structural analysis as in traditional SEM (Hulland, 1999). Another reason for choosing PLS-SEM is that the covariance-based SEM is rather sensitive to skewed distributions, multi-collinearity and misspecification in the model (Bollen, 1989; Cassel *et al.*, 1999), which may all be the case here. PLS-SEM is also particularly suited when sample sizes are small (Bagozzi, 2010) and when the analysis is tentative and predictive (Hair *et al.*, 2012; Wold, 1980). An accepted systematic application is a two-step process, encompassing the assessment of the measurement model (the outer model) and the assessment of the structural model (the inner model). The second stage is done using bootstrapping (Efron, 1994). We use Smart-PLS (partial least squares latent variable modeling approach) version 3.2.2.-M3 to test different types of casual relationships.

Model 1 - focus on outcome from the course

Due to the exploratory nature of this study, we have not made any hypotheses a priori. Instead, we have searched for a model that is able to show the level of data support in order to discuss certain aspects of the learning process in the course as a whole as experienced by the students and to discuss the specific leaning outcome on specific elements of the course.

Clearly, any teaching activity should be controlled by a clear view on the means to achieve the goal of actually learning something and not just ending up having had an experience. Given the timeframe of the course to take place, the present course 'Dynamic Performance and Data Driven Modeling' aims at giving the students an applicable knowledge of relevant concepts and tools and some training in using this knowledge actively on real data. The course requires some previous knowledge, which for now is covered under the heading 'Basic Skills'. Here we expect the student to have a good general knowledge about economic thinking, specific basic knowledge of the Balanced Scorecard thinking (BSC), good statistical knowledge up to and including multiple linear regression and good skills in handling Excel as a fundamental data processing tool.

The course then aims at extending the students' knowledge on two dimensions. Both deal with the full process from 'data to decision', but one dimension/stream implicitly includes the time dimension, whereas the other teaching stream works explicitly on the time dimension.

The first stream is working directly on the overall BSC as a structural setup and understanding of firms. Causality is present in the discussions, but the focus is the randomness that can be measured in the various BSC-KPIs and their possible relation to future performance measurements (profit, ROI etc.) under the perspective of random and risk assumptions. The data processing method is primarily the Monte-Carlo method, and the specific tool is @Risk.

The second stream also starts in the BSC thinking setup, but works from the core of different perspectives and tries to figure out the specific and detailed dynamics of the various data/decision driven modeling examples. The method is in this case based on System Dynamics Modeling (SDM), which covers both a conceptual aspect relating to the understanding of causality (essentially Newtonian), but also handles time (either continuous or discrete) explicitly in its associated simulation setups. The tools used for handling SDM are both VENSIM and Excel. There is, in fact, a relatively simple one-to-one relation between an SDM model in VENSIM and Excel in the case of an explicit discrete time representation that is where observations are typically represented as time series data.

In addition, we carefully contemplated the pedagogical principles required in order to support a strong learning process. Over the years, our approach has become more and more practical in the sense that a theoretical element is always followed by practical hands-on exercises. That means that we have in fact activated three types of hands-on activities by now – *(A)* the theory presented is accompanied by examples (students have hands-on as homework) (13.Que), and *(B)* two kinds of regular workshops, where (A) is structured workshops (14. Que) and (B) is unstructured workshops (15. Que). The unstructured workshops are followed by serious de-briefing activities (resulting also in hands-on homework for the students).

Therefore, our aim is to construct a well-functioning model that can help improve our understanding of the 15 questions and their relationships, specified in a number of latent and manifest variables related to our objectives for the course (Barclay *et al.*, 1995). The goal of model selection in SEM is to find a useful approximating model that (a) fits well, (b) has easily interpretable parameters, (c) approximates reality in as parsimonious a fashion as possible, and (d) can be used for further inference and prediction (Preacher and Merkle, 2012). This is in line with the recommendations from previous research using structural equation modeling and performance management (see, e.g., the discussion in Bedford and Speklé, 2018; Bisbe *et al.*, 2007; Hall and Smith, 2009; Hartmann and Maas, 2011). This is also in line with Hair *et al.* (2017), who said that: "*researchers typically prefer models that are good at explaining the data (thus, with high R^2 values) but also have fewer exogenous constructs. Such models are called parsimonious*" (Hair *et al.*, 2017, p. 209). We have chosen a very pragmatic approach that is to find a model design that actually works and a model that can be explained in simple terms in relation to our objectives for the course. We simultaneously test the structural model and the measurement model using Smart-PLS. All constructs in our study are measured as multi-dimensional constructs consisting of a series of observable indicators (manifest variables) (Bedford and Speklé, 2018).

Figure 15 shows the overall results from the measurement and structural model, including the test of three alternative paths (shown as dotted lines). These alternative paths did not show any statistically significant effect. Because the students have not previously used neither @Risk nor the VENSIM software in their study program, these relationships do not seem relevant.

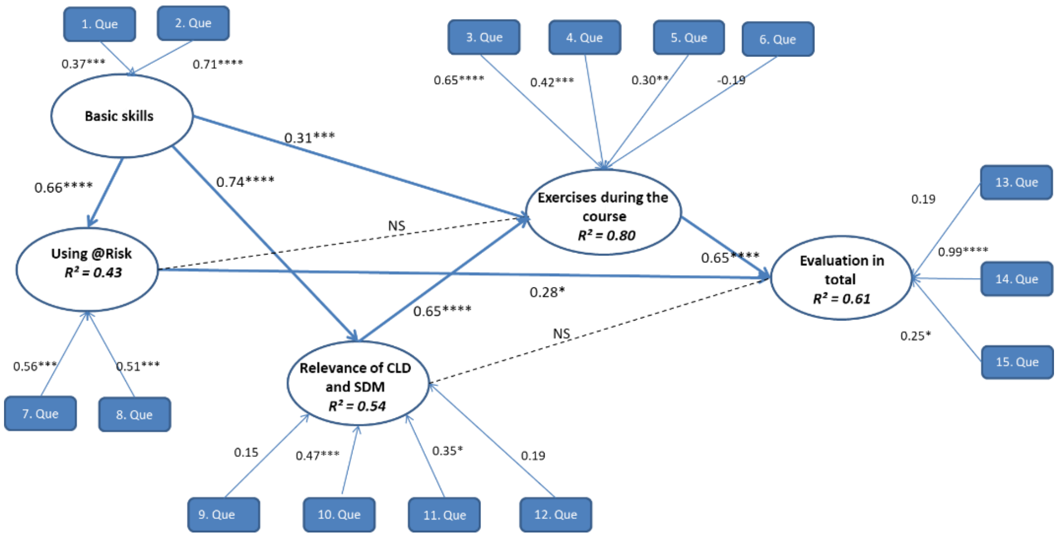

Figure 15: The optimal path model

Notes: **t*-statistic > 1.64 is significant at $p < 0.10$ level; ***t*-statistic > 1.96 is significant at $p < 0.05$ level; ****t*-statistic > 2.58 is significant at $p < 0.01$ level; *****t*-statistic > 3.29 is significant at $p < 0.001$ level.

Statisticians proficient in SEM have commented that researchers within the social sciences often fail to test alternative relations to the proposed model (e.g., Boomsma, 2000; Steiger, 2001). The best way for researchers to address this is to present some alternative models (for example by pretesting the data) or to design one or more theoretically plausible models that represent competing hypotheses from existing literature, which we also did, but we ended up with the model shown in Figure 15.

We only use formative measures (i.e. causality is from measures to the construct) and not reflective measures (i.e. reverse causality). The use of formative indicators tends to eliminate the need for the exogenous constructs, since all explanation is 'pushed' towards the endogenous variables (Hulland, 1999). Reflective indicators are typically used for classical test theory and factor analysis; they are invoked in an attempt to account for observed variances or covariances, whereas formative indicators, in contrast, are not designed to account for observed variables; they are used to minimize residuals in the structural relationship (Fornell and Bookstein, 1982). In line with the model assumption in Fornell *et al.* (1990), we see the indicators as formative for all five latent structures including our latent construct ‘evaluation’[21].

Assessment of the measurement model

Most items in the formative constructs are statistically significant at different t-statistics, indicating their significant contribution to the measured construct (R^2 for all formative constructs ≥ 0.50 except for ‘Using @Risk’, meaning that these constructs contribute at a sufficient degree to its intended content (Chin, 1998). As can be seen from Figure 15, our manifest loadings are statistically significant at different levels ranging from 0.001 to 0.10. However, some questions do not have any effect in the model (6. Que, 9. Que,

[21]We did additional tests similar to those reported in prior studies (e.g., Berger and Boritz, 2012; Fornell *et al.*, 1990) whereby we examined different alternative measurement models, modeling all constructs in the model as formative, all the constructs as reflective, and various models with different constructs modeled as formative or reflective. All these tests show very similar results as those reported in this paper (only minor differences in loadings exist). These tests suggest that the result is not really driven by how the constructs are modeled.

12. Que, and 13. Que). Because of the small number of observations and only 15 questions, we have not removed the non-statistically manifest variables from the model, which is normally the case when using hypotheses.

Because the formative measurement construct is based on multiple regressions, the manifest variables in a formative construct should also be tested for multi-collinearity (Diamantopoulos and Winklhofer, 2001). We have used the variance inflation factor (VIF) for this test (Grewal *et al.*, 2004). To test the formative construct validity, we assess the indicators' weight rather than the loadings. As a rule of thumb, a VIF greater than 3.3 indicates multi-collinearity (Petter, 2007). The result from Smart-PLS shows that none of the formative measures exceeds this threshold.

Table 4 shows the result for discriminant validity indicating that all latent variables are closely related. This is not surprising in cases with few questions and a small sample (e.g., when you work without much guidance, or when the results only concern users' interests (Roberts and Thatcher, 2009)).

	Inter-Construct Correlation and Square Root of Average Variance Extracted Statistics a)				
	Constructs with Formative Indicators				
	(1)	**(2)**	**(3)**	**(4)**	**(5)**
(1)Basic skills	**1**				
(2)Evaluation in total	0.690	**1**			
(3)Relevance of CLS & SDM	0.731	0.737	**1**		
(4)Relevant exercises during the course	0.780	0.810	0.871	**1**	
(5)Using @Risk	0.653	0.663	0.674	0.602	**1**

[a] Diagonal values are the square roots of AVE. Off-diagonal values are the correlations between the latent variables calculated in Smart-PLS. AVE is only relevant when constructs are measured with reflective indicators (Barclay *et al.*, 1995) .

Table 4: Inter-construct correlation and square root of average variance extracted statistics

The output from Smart-PLS in relation to the measurement model verifies the initial results from our previous design model. However, the categorization of a construct as being formative or reflective is not always clear-cut and is much influenced by the researcher's judgment (see, e.g., Hair *et al.*, 2017, chap. 2). One important characteristic of formative indicators is that they are not interchangeable as are reflective indicators. Thus, each indicator for a formative construct captures a specific aspect of the construct's domain. Taken jointly, as we have done here, the indicators ultimately determine the meaning of the construct, which implies that leaving out an indicator potentially alters the nature of the construct fundamentally.

Assessment of the structural model

We use Smart-PLS with bootstrapping as a resampling technique to estimate the structural model and the significance of the paths. We use path coefficients and the R^2 jointly to evaluate the model (Chin, 1998). Table 5 shows the output from Smart-PLS together with the *t*-statistics. Figure 15 includes this information (1,000 resamples) including the path coefficients and their associated *t*-values (Efron, 1994). R^2 is the overall effect size measure of an endogenous latent variable, indicating here that the model explains 61% of the 'Evaluation in total' (the response variables) so that the model as a whole can be seen as a relatively good model (Gefen and Straub, 2005; Hair *et al.*, 2017).

Path coefficients: test and control variables		
	Path coefficient	**t-statistics**
Basic skills -> Exercises during the course	0.31	2.42***
Basic skills -> Relevance of CLD/SDM	0.73	9.42****
Basic skills -> Using @Risk	0.65	6.28****
Using @Risk -> Evaluation in total	0.28	1.86*
Using @Risk -> Exercises during the course	0.01	N/S
Relevance of CLD and SDM -> Exercises during the course	0.65	5.70****
Relevance of CLD and SDM -> Evaluation in total	0.08	N/S
Exercises during the course -> Evaluation in total	0.65	5.91****

Notes: **t-statistic > 1.64 is significant at p < 0.10 level; **t-statistic >1.96 is significant at p < 0.05 level; ***t-statistic > 2.58 is significant at p < 0.01 level; ****t-statistic > 3.29 is significant at p < 0.001 level.*

Table 5: Path coefficients and t-statistics

Figure 15 holds all the relevant information for the structural relations model. As can be seen from the results, the structural model also indicates 54% of ‘Relevance of CLS and SDM’, and 43% of ‘Using @Risk’, which means that these constructs can be explained with a relatively good fit.

For the model in general, Figure 15 shows that the parameter ‘basic skills’ influences both ‘exercises during the course’, ‘relevance of CLD & SDM’, and the ‘use of the @Risk’ software. In fact, this is not surprising, however, but quite important. It actually means that students’ a-priory ‘basic knowledge’ must include not only the knowledge, but also the right skills (i.e., being able to use different statistics tools and techniques as assumed as prerequisites for the course) and being able to transform the knowledge and skills to the new environment of data driven modeling (Ballou *et al.,* 2018).

Surprisingly, the latent variable of ‘using @Risk’ does not have a strong effect on ‘exercises during the course’, but instead seems to have a direct effect on the ‘evaluation in total’. This seems to indicate that Monte Carlo simulation through @Risk has been understood primarily at the theoretical level than at the practical level. One problem we discovered later on during the course was that several students had problems with the installation of @Risk and getting it running. These disturbing elements may have jeopardized actually using @Risk for different types of decisions during the course.

It seems that the latent variable ‘exercises during the course’ is very relevant for the ‘CLD and SDM’ construct as a form of mediation. In short, mediation occurs when a third variable, referred to as a mediator variable (here ‘exercises during the course’), intervenes between two other related constructs (here ‘relevance of CLD & SDM’ and ‘evaluation in total’). More precisely, a change in the exogenous construct results in a change of the mediator variable, which, in turn, changes the endogenous construct (Hair *et al.,* 2017). However, looking into the question items for our response variable, we note that ‘hands-on exercises in total for the course’ (14. Que) has the most important effect on this construct. ‘Exercises related to different scientific issues’ (13. Que) and ‘hands-on in our two workshops’ (15. Que) do have a minor effect and no effect at all, respectively. It does seem surprising that the workshops (unstructured) do not have any impact on the output evaluation. Workshops with a more structured set-up (hands-on exercises of various kinds, 13. Que and 14 .Que) show strong effects (see, e.g., Everaert *et al.*, 2008).

Especially our teaching of SDM has utilized structured workshops largely, where theory (homework for the students) is presented in the form of both Excel (basic skills) and VENSIM (new skills), so the results are really encouraging as the confirm our pedagogic approach.

Model 2 - focus on system dynamics and @Risk

Specifically for exploratory studies, researchers design alternative SEM models in order to be able to give a broader picture of the results (see, e.g., Hartmann and Mass, 2011 and Bisbe and Chenhall, 2007). An interesting and alternative model in this study could be to test our two software programs (@Risk and VENSIM) as response variables. Figure 17 shows the result of this alternative PLS-SEM model.

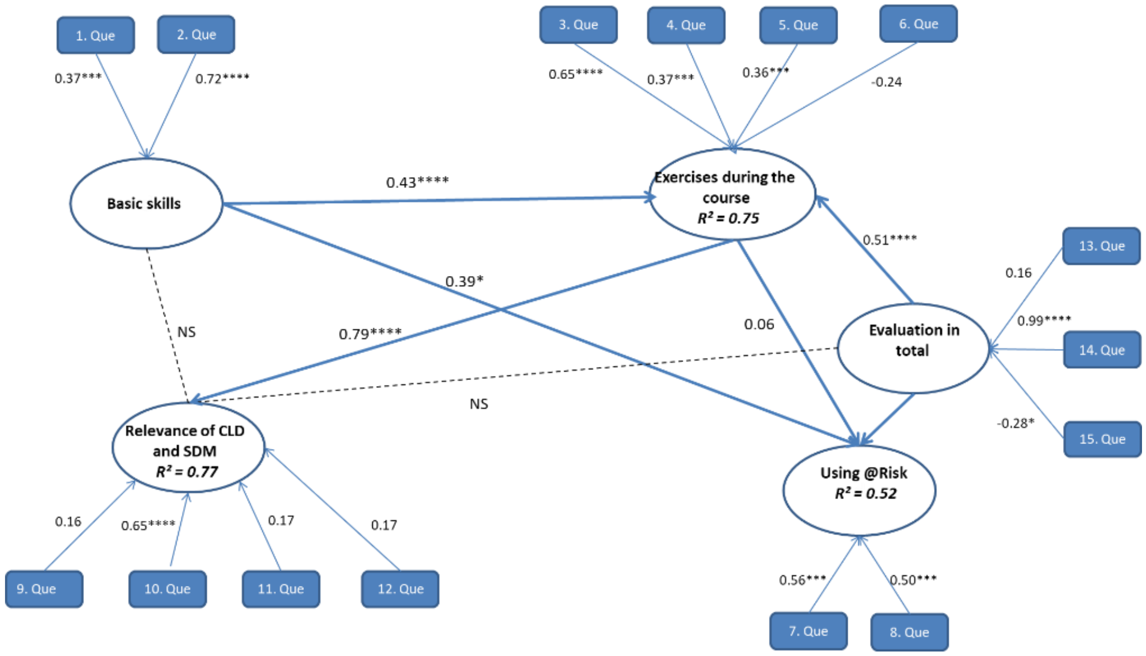

Figure 16: An alternative model

Several interesting messages show up in this reformulation of the interaction of the teaching elements. First, the association between 'Basic Skills' and 'Relevance of CLD & SDM' is less dominant. Clearly, 'Relevance of CLD & SDM' covers much new information. The previous model (Figure 16) demonstrated that much of the students' understanding of SDM came from the incorporation of SDM thinking in the 'structured exercises' that are part of the 'Relevant exercises during the course'. In combination, the two models tell us that we have a really strong two-way interaction between 'Relevant exercises during the course' and 'Relevance of CLD & SDM', which actually constitutes a 'mission completed' for this activity in the course.

Secondly, 'Using @Risk' is primarily related to 'Basic Skills' and 'Evaluation in total'. In fact, the really interesting message is that 'Using @Risk' has been taken in by the students at the more theoretical level, not so much at the practical level, but this is also to be expected as mentioned earlier. Clearly, the objective of the course is to provide the students with concepts and tools that enable them to work in practice in both streams. This means that we provide a framework for the students to engage in actual data-driven modeling activities measuring performance on important economic dimensions, taking both risk and dynamic complexity aspects into account for decision support.

As regards future pedagogical evaluations, our experiments above have showed that specific questions about the students' prior knowledge are necessary. For example, a separation of the basic BSC knowledge and the teaching/learning-effect of the new knowledge dealt with in the course is important information in order to get insights into how much the activation of the theory adds to the more in-depth understanding by the students. The same goes for techniques such as Multiple Linear Regression. At the formal level, the students' prior knowledge is, in fact, very impressive, but when it comes to actually activating it in practical use, we see a wide range of shortcomings, which we have to deal with in the process, of course. It would therefore be nice to be able to separate this effect from other effects.

Another hurdle is that students typically seem to believe that ‘theory’ is the most important aspect in a course, and that reality is merely ‘messy’ information that is difficult to interpret. Therefore, when we confront the students with real data, they typically have great trouble to see how to use theory as a helper in order to extract actual information from the data on hand. We would also like to ask questions in the future to assess to what degree we succeed in this mind-blowing turn-around. It is not unreasonable to think that the students are somewhat ‘damaged’ by all the theory-focused teaching they have received up until now.

Finally, it has been a surprise to at least one of the teachers in this course, how much a Structural Equation Model by Partial Least Squares actually can tell us, based as it is on a not so large questionnaire sample.

We have used the questionnaire as a conventional data interpretation instrument focused on means and ends, and this does not prove anything (whatever that means), but we do get some indications and advice as to what can and should be changed and what actually works. The course essentially performs well and works pretty much as intended.

E. Conclusions and future perspectives

Integrating Business Analytics into organizational performance measurement and management has been a good and an exciting experience for both lecturers and students, but also one that requires a lot of time (especially for the lecturers, anyway). Specifically for hands-on exercises during the course, but also for preparing workshops.

Research publication (i.e., metrics and journal-ranking classifications) is no longer the focal point of governments. Instead, they require research to have a demonstrable impact on society. Research evaluation exercises undertaken in countries such as the UK, Australia, New Zealand, Sweden, China, and Canada now underscore the significance of demonstrating the impact of research on practice (Tharapos and Marriott, 2020 and Tucker & Lawson, 2020). Besides, the allocation of government funding will increasingly be influenced by the economic, social and other benefits of university research through an impact and engagement evaluation framework. One thing is finding the best approaches to teaching a course with many ‘new’ concepts and ideas; another is to be able to heighten the interest and the outcome for the students.

The result of our student survey shows a promising effect from different topics taught in helping students with practicing the ‘learning by doing’ methodology, engaging students in learning and interacting with not only data, but also with the problems and dilemmas of making fact-based decisions from (small) datasets. However, it evidently requires a high degree of dedication by the students to fully understand the data-driven analytics approach and to be able to actually make decisions based on this information.

A recurring problem is how to choose the right technique for the problem the students try to solve. However, perhaps the most important issue for moving into a data-driven decision-making paradigm for teaching is that the students are able to see the problems in a coherent framework and are able to combine different, often separated, issues with each other. For future courses, we have learnt that it is necessary to increase the depth of the ‘data-mining’ and ‘machine learning’ techniques for performance management. Several surveys have shown that decision-makers and employees need to have the right skills for doing data analysis (see e.g., IMA, 2013; Deloitte, 2015; Simchi-Levi, 2014; WEF, 2016), and these topics seem to gain increased importance. For the future our intention, therefore, is better being able to link a specific topic to the ‘right’ techniques.

Performance measurement and management, accounting and supply-chain management are currently experiencing rapid technological change.

All professions are faced with infinite new technological opportunities such as cloud-based solutions, increased business intelligence, data analytics, and Blockchain. In the future, new and increased expertise in technology-related skills will be crucial, as will the associated professional skills to navigate in a world of data and decisions, successfully.

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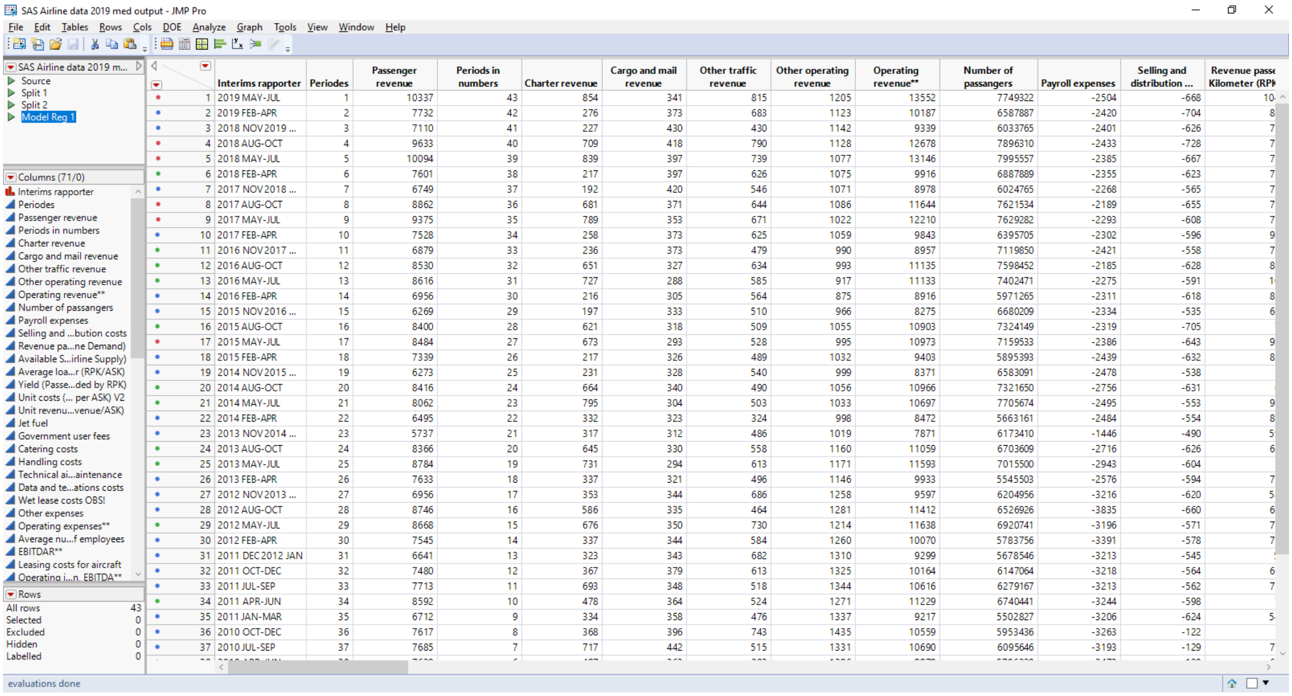
Appendix A: Teaching Plan for Dynamic Performance and Data-driven Modelling

Course: Dynamic Performance and Data-driven Modelling				
Week		Stream A+B		
1	X+Y	Introduction to the course – (A-stream) “BSC Analytics” and (B-stream) “System Dynamics” thinking We look closer into: • Course description • Over view for the course • Over view for the software used in the course • Various [(1) https://www.emu.dk/modul/vensim, (2) http://vensim.com/ …]		
	Person	**Section A** **Themes, cases etc.**	Person	**Section B** **Themes, cases etc.**
2	X	**Introduction to holistic holistic performance model and the BSC model:** Lit: Kaplan and Norton (2008), and Soderberg *et al.*, (2011). **Exercises/case:** Three miner exercises in BSC Discussion of points & assumptions	Y	*This article* ***”Some Basic Concepts in System Dynamics”, Jay W. Forrester*** *Sloan School of Management* *Massachusetts Institute of Technology* *(see link – below)*
3	X	**Introduction to Perf Man, BA:** Lit: Davenport & SAS Institute (2008) og PWC (2013). **Example/case:** Variables, input/output, cause-and-effect, *Big Airlines Part 1* (using SAS JMP and Data Analysis in excel) Discussion of points & assumptions	Y	**Dynamic Performance and Stock-Flow identities**, in SD-terms Level-Rates. Themes: • Time-chart thinking. • How flows drive stocks. We will work with the article: “Improving strategic management with the fundamental principles of system dynamics”, Kim Warren (329-341) *(link – see below)*
4	X	**Mapping Key Performance Indicators i performance management:** Lit: Kaplan and Norton: Mapping the strategy (2000) **Example/case:** Cluster and discriminant analysis *Big Airlines Part 2* (using SAS JMP) Discussion of points & assumptions	Y	**Dynamic Excel models for** simple Prod/inventory. **Both Excel and VENSIM versions** will be used ... VENSIM must be installed. http://vensim.com/free-download/ Go to VENSIM help // Contents // User Guide -- Vensim Introduction and Tutorials To get an intro to VENSIMs bottom functionality
5	X	**Mapping, KPIs and exploratory factor analysis and strategy:** Lit.: Kaplan and Norton (1996) and Castello and Osborne (2005) **Example/case:** Company XYZ using SAS JMP Discussion of points & assumptions	Y	**A System Dynamic Model developed step-by-step** in VENSIM – we will work with the content of the article *“Developing System Dynamics Models with “Step-By-Step” Approach”* (14.pdf) https://hrcak.srce.hr/file/33789
6	X	**Test og prediktion af metrics og KPIs:** Lit: Schmueli and Koppius (2011) **Example/case:** Multiple regression and prediction for Big Group Bank Discussion of points & assumptions	Y	**CLD-diagrams, CLD-SD converting** (Excel or VENSIM), parameters determination, Correlation, Regression … Article: *“Diagramming Conventions in System Dynamics”, David C. Lane, University of Reading* *(link – see below)*
7	X	**Using qualitative variable and KPIs:** Lit: Announced later… **Example/case:** Log regression etc. Discussion of points & assumptions	Y	**DATA-CLD-SD-Case … From Data to Model** … Data Driven Modeling *Note /WP will be uploaded to Blackboard*
8	X+Y	***Workshop mainly with a conceptual content***		
9	X	**Intro to @Risk + different types of analysis:** Lit: Announced later…+ manuals **Example/case:** Analysis of business Discussion of points & assumptions	Y	***Workshop debriefing ...***
10	X	**Profitability with the Activity-based Profit Analysis model (using @Risk):**	Y	***Workshop debriefing ...***

		Lit: Cooper and Kaplan 1991 & Gribbin Lau and Lau 1996 **<u>Example/case:</u>** Classic Pen Company Discussion of points & assumptions		
11	X	**<u>TD-ABC revised into a stochastic simulation approach (using @Risk):</u>** Lit.: Kaplan & Anderson (2004). **<u>Example/case:</u>** Example from Anderson & Kaplan (2004) Discussion of points & assumptions	Y	**Dynamic Performance and Stock-Flow identities**, In SD-terms Level-Rates. • ”The problem of causality” • LEAD/LAG in BSC thinking • Complexity, correlation, Regression … *“Improving strategic management with the fundamental principles of system dynamics”, Kim Warren* (341 mid-on page - 349) *(link – see below)*
12	X	**<u>Optimization of and ABC model and building a simple performance model using @Risk:</u>** Lit: Silvestro (2016) (the short version) and Valmohammadi and Servati, (2010) **<u>Eexercises/case:</u>** Optimization of an ABC model (continuation of Classic Pen Company) + Test of the strategy and building a simple performance model from this Discussion of points & assumptions	Y	***“Dynamic equilibrium dynamics” and other analysis (STEP, RAMP, SIN – demand)***
13	X	**<u>Budget simulation and optimization (using @Risk):</u>** Lit.: Barket *et al.* (2009) Zeller and Metzger (2013) (different relations - Sandalgaard and Bukh, 2008) **<u>Excercises/case:</u>** The Integrated Budget Model Discussion of points & assumptions	Y	**Methodological “no-trends” and “trends” ...** *Warren, K. (2004). “Why has feedback systems thinking struggled to influence strategy and policy formulation? Suggestive evidence, explanations and solutions.”* Systems Research & Behavioral Science, 21(4), 331-347. *Barnabè, F., & Busco, C. (2012). The causal relationships between performance drivers and outcomes.* Journal of Accounting & Organizational Change, 8(4), 528-538. *(link – see below)*
14	X	**<u>KPIs over time (using @Risk):</u>** Lit.: Announced later…+ manuals **<u>Example/case:</u>** The Time Company Model Discussion of points & assumptions	Y	*Simchi-Levi, D. (2014). OM Forum—OM research: “From problem-driven to data-driven research”.* Manufacturing and Service Operations Management, 16(1), 2-10. *(link – see below)*
15	X	**<u>BSC and TD-ABC - simulation and optimization:</u>** Lit: S. Nielsen (2017) WP **<u>Example/case:</u>** BSC and TD-ABC Discussion of points & assumptions	Y	***Workshop preparations …***
16	X+Y	***Workshop mainly with a methodology content***		

Appendix B: Extract Datasets used for Workshops

The SAS Airline dataset: Clearly, the starting point has to be the empirical material available. In SAS Pro it is possible to design a script/code for each scenarios the student wants to conduct. We show an example of this below.



	Interims rapporter	Periodes	Passenger revenue	Periods in numbers	Charter revenue	Cargo and mail revenue	Other traffic revenue	Other operating revenue	Operating revenue**	Number of passangers	Payroll expenses	Selling and distribution ...	Revenue passe Kilometer (RPK
1	2019 MAY-JUL	1	10337	43	854	341	815	1205	13552	7749322	-2504	-668	10
2	2019 FEB-APR	2	7732	42	276	373	683	1123	10187	6587887	-2420	-704	8
3	2018 NOV 2019 ...	3	7110	41	227	430	430	1142	9339	6033765	-2401	-626	7
4	2018 AUG-OCT	4	9633	40	709	418	790	1128	12678	7896310	-2433	-728	7
5	2018 MAY-JUL	5	10094	39	839	397	739	1077	13146	7995557	-2385	-667	7
6	2018 FEB-APR	6	7601	38	217	397	626	1075	9916	6887889	-2355	-623	7
7	2017 NOV 2018 ...	7	6749	37	192	420	546	1071	8978	6024765	-2268	-565	7
8	2017 AUG-OCT	8	8862	36	681	371	644	1086	11644	7621534	-2189	-655	7
9	2017 MAY-JUL	9	9375	35	789	353	671	1022	12210	7629282	-2293	-608	7
10	2017 FEB-APR	10	7528	34	258	373	625	1059	9843	6395705	-2302	-596	9
11	2016 NOV 2017 ...	11	6879	33	236	373	479	990	8957	7119850	-2421	-558	7
12	2016 AUG-OCT	12	8530	32	651	327	634	993	11135	7598452	-2185	-628	8
13	2016 MAY-JUL	13	8616	31	727	288	585	917	11133	7402471	-2275	-591	1
14	2016 FEB-APR	14	6956	30	216	305	564	875	8916	5971265	-2311	-618	8
15	2015 NOV 2016 ...	15	6269	29	197	333	510	966	8275	6680209	-2334	-535	6
16	2015 AUG-OCT	16	8400	28	621	318	509	1055	10903	7324149	-2319	-705	
17	2015 MAY-JUL	17	8484	27	673	293	528	995	10973	7159533	-2386	-643	9
18	2015 FEB-APR	18	7339	26	217	326	489	1032	9403	5895393	-2439	-632	8
19	2014 NOV 2015 ...	19	6273	25	231	328	540	999	8371	6583091	-2478	-538	
20	2014 AUG-OCT	20	8416	24	664	340	490	1056	10966	7321650	-2756	-631	
21	2014 MAY-JUL	21	8062	23	795	304	503	1033	10697	7705674	-2495	-553	9
22	2014 FEB-APR	22	6495	22	332	323	324	998	8472	5663161	-2484	-554	8
23	2013 NOV 2014 ...	23	5737	21	317	312	486	1019	7871	6173410	-1446	-490	5
24	2013 AUG-OCT	24	8366	20	645	330	558	1160	11059	6703609	-2716	-626	6
25	2013 MAY-JUL	25	8784	19	731	294	613	1171	11593	7015500	-2943	-604	
26	2013 FEB-APR	26	7633	18	337	321	496	1146	9933	5545503	-2576	-594	7
27	2012 NOV 2013 ...	27	6956	17	353	344	686	1258	9597	6204956	-3216	-620	5
28	2012 AUG-OCT	28	8746	16	586	335	464	1281	11412	6526926	-3835	-660	6
29	2012 MAY-JUL	29	8668	15	676	350	730	1214	11638	6920741	-3196	-571	7
30	2012 FEB-APR	30	7545	14	337	344	584	1260	10070	5783756	-3391	-578	7
31	2011 DEC 2012 JAN	31	6641	13	323	343	682	1310	9299	5678546	-3213	-545	
32	2011 OCT-DEC	32	7480	12	367	379	613	1325	10164	6147064	-3218	-564	6
33	2011 JUL-SEP	33	7713	11	693	348	518	1344	10616	6279167	-3213	-562	7
34	2011 APR-JUN	34	8592	10	478	364	524	1271	11229	6740441	-3244	-598	
35	2011 JAN-MAR	35	6712	9	334	358	476	1337	9217	5502827	-3206	-624	5
36	2010 OCT-DEC	36	7617	8	368	396	743	1435	10559	5953436	-3263	-122	
37	2010 JUL-SEP	37	7685	7	717	442	515	1331	10690	6095646	-3193	-129	7

For example the script code for doing a regression model:

```
Fit Model(
               Y( :Passenger revenue ),
               Effects(
                              :Name( "Revenue passenger Kilometer (RPK or Airline Demand)" ),
                              :Name( "Available Seat Kilometer (ASK or Airline Supply)" ),
                              :Average number of employees
               ),
               Personality( "Standard Least Squares" ),
               Emphasis( "Effect Leverage" ),
               Run(
                              :Passenger revenue << {Summary of Fit( 1 ), Analysis of Variance( 1 ),
                              Parameter Estimates( 1 ), Lack of Fit( 0 ), Scaled Estimates( 0 ),
                              Plot Actual by Predicted( 1 ), Plot Regression( 0 ),
                              Plot Residual by Predicted( 1 ), Plot Studentized Residuals( 0 ),
                              Plot Effect Leverage( 1 ), Plot Residual by Normal Quantiles( 0 ),
                              Box Cox Y Transformation( 0 )}
               ))
```

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