Teaching Data Driven Innovation – Facing a Challenge for Higher Education

Full Paper

Barbara Dinter
Chemnitz University of Technology
barbara.dinter@wirtschaft.tu-chemnitz.de

Christoph Kollwitz
Chemnitz University of Technology
christoph.kollwitz@wirtschaft.tu-chemnitz.de

Albrecht Fritzsche
Friedrich-Alexander-University Erlangen-Nuremberg
albrecht.fritzsche@fau.de

Abstract

In the era of digitization, data has become a very important resource for competition. To generate value from these constantly growing amounts of data and to create innovative services and business models based on the data, organizations need to rely on well-trained data scientists and analysts. The required skill set for such experts is complex and challenges higher education in the information systems discipline. Despite some first and promising efforts, there is still a lack of novel teaching approaches for data driven innovation. In this paper we design a morphological box providing a solution space for teaching data driven innovation at universities. For the systematization we analyze the submissions of an academic analytics contest and combine our findings with the existing knowledge base. Furthermore, we present our learnings from two teaching cases and reflect our experiences when applying them in class.

Keywords

Data driven innovation, big data, analytics, teaching practices, educational research.

Introduction

Driven by the ongoing digitization of business and society, large amounts of data are generated all over the world. Big data and related analytics technologies set new requirements for organizations to compete in the global economy (Manyika et al. 2011). Enterprises recognize big data more and more as valuable resources for the development of innovative services and as the foundation for new business models (Hartmann et al. 2016). As a result, the demand for well-trained data scientists and analysts from industry is constantly growing and is becoming a serious challenge for higher education (Davenport and Patil 2012). In recent time, this shortage has already been addressed by the development of various information systems (IS) curricula (e.g. Cegielski and Jones-Farmer 2016; Wixom et al. 2014) and IS competency models (e.g. Topi et al. 2017) dealing explicitly with big data & analytics. However, to generate most business value from the potential of big data & analytics, organizations need to foster new approaches to data driven innovation rather than just optimizing existing use cases and business models by means of modern analytics. Therefore, data scientist profiles require competencies such as creativity and human intuition in addition to skills in analytics, statistics and computer science (Provost and Fawcett 2013). Fichman et al. (2014) follow a similar argumentation when they consider competencies in digital innovation as not only relevant for IS students, but also as an essential component of educating business students.

In contrast to such requirements, the challenge of teaching data driven innovation by combining and applying methods from several disciplines, has - to the best of our knowledge - not been addressed in detail so far. In accordance with Wang (2015), who considers innovative teaching methods and cases in the field of big data & analytics education as not sufficiently discussed in IS research, we see a need to support faculty in identifying novel teaching approaches for data driven innovation. Therefore, our research question can be formulated as follows: How can data driven innovation be taught in class?

To answer this question, we draw on existing literature and the empirical analysis of an academic analytics contest for systematizing the various teaching options by means of a morphological box. Therefore, we apply the general morphological analysis (GMA), an approach which is suitable for structuring complex socio-technical problems and the subsequent systematic derivation of solutions (Ritchey 2011). The morphological box presents the parameters describing the teaching options and provides a better theoretical understanding of data driven innovation. Moreover, we describe two hands-on teaching cases, in which we have gained experiences in combining know-how from the field of big data & analytics with methods of innovation management in settings which have so far received little attention.

The paper is organized as follows. First, we give an overview about the theoretical underpinning and related work before describing our research method und the analysis of the analytics contest. Afterwards, the morphological box for teaching data driven innovation and its dimensions and attributes are presented. Subsequently, we describe two exemplary teaching cases for data driven innovation. Finally, we summarize our findings, discuss limitations of the paper and provide an outlook for our future work.

Foundations and Theoretical Underpinning

Next we provide an overview of the foundations and the state of the art of the research streams relevant for answering our research question in general and for designing the morphological box in detail.

Data Driven Innovation

The advent of big data & analytics and its resulting broad range of application opportunities have increased the options, but also the need for organizations to take advantage of such trends by developing new use cases and business models. Consequently, digital and data driven innovation becomes an essential component of organizational capabilities (Manyika et al. 2011). Whereas digital innovation can be understood in its broad sense as “a product, process, or business model that is perceived as new [...] and is embodied in or enabled by IT” (Fichman et al. 2014, p. 330), data-driven innovation (or data based innovation as a related term) is a business innovation that is “based on the use of data and analytics to innovate for growth and well-being” (Zolnowski et al. 2016, p. 3). Despite its relevance, only few scientific contributions, such as Vanauer et al. (2015), provide guidance how data driven innovation processes can be conducted. Previous contributions have rather focused on the nature of the resulting artifact – the data driven (or data based) business model, such as in Hartmann et al. (2016) and Zolnowski et al. (2016). Such lack of established data driven innovation methods emphasizes the need to educate students in this competency or – in other words – confirms the aforementioned research question.

Teaching Data-Driven Innovation

The huge demand for dedicated data scientists and analysts trained in big data & analytics has resulted in revised and new curricula (e.g. Gupta et al. 2015) as well as in a significant increase of dedicated programs at universities (in particular on master level). As the recent MSIS 2016 Global Competency Model for Graduate Degree Programs in Information Systems (MSIS 2016) illustrates, competencies in the area of data, information and content management , encompassing skills about big data & analytics, as well as competencies in the area of innovation, organizational change and entrepreneurship and creativity as an individual foundational competency constitute major competency areas in IS education (Topi et al. 2017). Further contributions investigate job profiles, representing the industry demand, and the corresponding skills that should be taught at universities (e.g. Debortoli et al. 2014). Summarizing, previous work about big data & analytics education rather focuses on what to teach but not how.

Compared to the topic of big data & analytics education less contributions address how innovation can be taught. Trifilova et al. (2016) provide a good overview of various teaching approaches for innovation and entrepreneurship. While Fichman et al (2014) discuss the role of digital innovation in the IS curriculum in general, very few (if at all) contributions investigate approaches for teaching data driven innovation in particular. Some insights can be gained from publications presenting data driven innovation approaches that can also be used as a teaching format in class, such as hackathons. By designing a morphological box and presenting two exemplary cases of data driven innovation courses we try to close the gap of missing guidance for faculty teaching this topic.

Pedagogical Approach

Knowledge acquisition and learning in the context of the digital transformation is a complex process which cannot be reduced to simple adoption (Fritzsche and Oks 2016). For a better understanding of different learning objectives and outcomes, Bloom's Taxonomy (Bloom 1956) has become a widely used standard, covering six different dimensions which are referred to as knowledge, comprehension, application, analysis, synthesis, and evaluation. For a further distinction of knowledge content on the one hand and its application in practice on the other hand, Krathwohl (2002) has elaborated the taxonomy into a two-dimensional framework. In the knowledge dimension, the framework distinguishes factual knowledge concerning simple, explicit items of information, conceptual knowledge concerning wider cognitive schemes of interconnected items, procedural knowledge regarding the operations necessary to perform actions, and metacognitive knowledge which takes self-reflective aspects of knowledge and awareness of one's own resources into consideration,. In the application dimension it distinguishes six different types of cognition with respect to the kind of acts in which they are applied: remembering, understanding, applying, analyzing, evaluating and creating.

The abovementioned taxonomies of learning objectives have proven useful for the design of Business Analytics (BA) and Business Intelligence (BI) curricula on various occasions. Marjanovic (2012), for example, has used Bloom's Taxonomy to design a teaching format based on a scaffolding approach in which teachers include active student activities in their courses (cf. Collins et al. 1991). Gupta et al.(2015) have applied Krathwohl's two-dimensional model to analyze and adapt BI curricula on the undergraduate, graduate and MBA levels. Deng et al. (2016) have recently used Krathwohl's model to perform a comparative analysis of educational programs in BA for students with different business training. Little attention, however, has been paid so far to the application of the taxonomies in the context of teaching courses and programs for innovation in the field of big data & analytics. Practical experience with alternative formats for innovation teaching and training suggests that workshop and laboratory settings are more suitable for the development of higher-level knowledge and application-oriented cognitive processes (e.g. Halverson and Sheridan 2014; Schön and Ebner 2014). A systematic evaluation of such teaching formats in comparison to others regarding their objectives and outcome has so far not been undertaken in the field of big data.

Research Method

Since data driven innovation is a fairly new phenomenon, which has emerged in practice, appropriate teaching methods in the IS discipline are still missing. To reveal various opportunities for academic education, we design a morphological box demonstrating the solution space and various parameters for teaching data driven innovation.

General Morphological Analysis

The GMA is a heuristic creativity technique developed by the Swiss astronomer Fritz Zwicky (1969). The method pursues the basic idea of decomposing a complex problem into single dimensions to bring it in a manageable structure and to subsequently present solutions which consist of combined characteristic attributes of the previously separated dimensions (Ritchey 2011). Meanwhile GMA has become an established method, which is applied in various research areas including the IS discipline. In particular, GMA supports the systematic development of a solution space which helps to structure creativity and to avoid expensive trial and error solutions seeking (Couger et al. 1993). We apply GMA (Ritchey 2011) for the design of the morphological box following the procedure model introduced by Zwicky (1969) with the following five stages: (1) Identify a problem, (2) define all possible dimensions, which affect the solution for the problem, (3) design a morphological box to specify all characteristic attributes per dimension, (4) analyze and refine the resulting combinations of characteristic attributes, and (5) pick the most suitable solution to solve the problem. In the context of our research, the morphological box constitutes the target artifact, representing the teaching options for data driven innovation. As mentioned before our (1) problem lies in the complex nature of data driven innovation and the variety of related teaching approaches in higher education. We focus on the GMA steps (2) and (3) to identify the dimensions and attributes, mainly based on two sources – from literature and from the empirical analysis of an academic analytics innovation contest. The latter is presented in detail in the following subsection.

For demonstrating and evaluating the usefulness of the designed artifact, the paper at hand discusses two teaching cases that we have applied in the past. Furthermore, the application of those cases contributes to the iterative improvement and evaluation of our morphological box. We draw back on our experience as faculty members, where we have explored data driven innovation with IS students from different perspectives. Among others, we have conducted a series of workshops and a student research project.

Data Collection and Empirical Analysis

To gain insights about real-world data from data driven innovation projects in higher education we analyzed the Teradata Analytics challenges, organized by the Teradata University Network (TUN) (Dinter and Kollwitz 2016). TUN is a web-based portal for faculty and students in big data & analytics, BI, data warehousing and database management. The network is led by industry experts and faculty from various universities who provide and share content. Since 2014 TUN runs annually an innovation contest, the so-called Analytics Challenge. In this contest student teams (from college or university undergraduate and graduate students) can submit the results of their BA research or application cases. Student projects can range from BA or marketing analytics to big data and data science. A selection committee evaluates the submissions, consisting of an extended abstract and a draft visualization. These materials describe the core elements of the research, including the problem being solved, its significance, the approach adopted, and some key results. Most student teams participated in the context of a course and under supervision of a faculty member. Therefore, we consider their submissions as a valuable and representative source of information how data driven innovation can be organized in class and by which criteria the approaches can be distinguished.

We analyzed a total of 58 submissions from the challenges in 2014, 2015, and 2016. Most submissions were handed in from US universities, two from Singapore and one from Canada. The analysis had two major objectives: on the one hand, to evaluate the dimensions and attributes of the morphological box that we could identify before by the literature review; on the other hand, to potentially identify additional dimensions or attributes that we could not derive by literature. For the analysis two researchers independently hand-coded all submissions based on a criteria catalog derived from literature with criteria (dimensions) about the team composition, the underlying data sources, the applied innovation / creativity technique, etc.. Afterwards, not only the very few different codings were discussed, we especially identified additional dimensions exhibiting different attributes across the submissions. The TUN contest seems suitable in our context, since we got a widely spread sample of submissions from different universities in different countries and with various teaching approaches. We have considered these dimensions as relevant for the morphological box for teaching data driven innovation and therefore added them to the artifact. The resulting dimensions from the literature review as well as from the empirical analysis will be presented in the following.

Design of the Morphological Box

As mentioned above, we draw back on two major sources for the design of the morphological box: the consolidated results of a literature review are combined with insights that we have gained by investigating the student submissions of the TUN Analytics Challenge representing data driven innovation projects in class settings. Due to the broad range of dimensions of the morphological box we have divided them in four categories. We use the term “course” as an umbrella for various shapes of teaching forms such as tutorials, seminars and projects. The identified dimensions and their attributes are highlighted in the following by *italic font*.

Teaching Method

Drawing on the extant literature by Krathwohl (2002) discussed above, we distinguish learning objectives in two dimensions, one referring to the forms of knowledge to be acquired, and the other to the cognitive processes during which knowledge becomes applied by the learners. The *knowledge* dimension covers declarative and reflective aspects. Similar to Krathwohl (2002), we distinguish *factual*, *conceptual*, *procedural*, and *metacognitive knowledge*. Regarding the *cognitive processes*, we distinguish *remembering*, *understanding*, *applying*, *analyzing*, *evaluating*, and *creating*. As the courses and programs are designed for experts who need to develop the ability to work autonomously as actors in data-driven innovation, we are particularly interested in the morphological differentiation of reflective aspects of knowledge on the one side and holistic, embedded cognitive processes like analysis, evaluation and creation on the other. The actual facts which are learnt and their remembrance as single bits of information therefore receive little attention. Instead, we focus on more general abilities which will make the learners capable to cope with the challenges of innovation on their own.

Furthermore, we distinguish the way how *content is presented*. Traditional teaching methods represent an *expository* approach, where teachers supply knowledge to students in unidirectional communication, usually by standing in front of them like an artist in front of an audience. Modern settings often take a more *explorative* approach by letting the students make experiences on their own and learn from them. In terms of *knowledge acquisition* teachers have the choice between *cumulative* designs where students successively acquire new knowledge piece by piece and *cyclic* designs where they return again and again to the same knowledge items, successively increase its granularity and ensure its correct remembrance.

Course Setting

The first category encompasses the dimensions related to the formal organization and conditions of the course setting. In accordance with Gupta et al. (2015) we capture in the dimension *level* if the participants are enrolled as *undergraduate*, *master* or *MBA* students. The dimension *course format* encompasses common shapes in higher education varying in duration and frequency as they can be found in literature (e.g. Topi et al. 2017) and are offered at most universities: *lecture, tutorial, workshop* and *project*. We add *hackathon* (in the context of data driven innovation also sometimes called datathon) (Anslow et al. 2016), *innovation lab* (Guthrie 2014) and *innovation contest* (Bullinger and Möslein 2010) as novel course settings for data driven innovation.

The analysis of the TUN Analytics Challenge has revealed further dimensions, some of them confirming previous literature: The *participants* can work as *individuals* as well as in a *team* in data driven innovation courses (Bullinger and Möslein 2010). The *team composition* indicates if students from various disciplines participate (*interdisciplinary*) or not (*monodisciplinary*). The last dimension considers the involvement *of third parties* within the course. For example, companies or non-governmental-organizations (NGOs) can provide case studies or data sets from practice and thus, contribute to an authentic and practical course setting.

Course Content

In our context the category course content encompasses dimensions that describe which aspects of big data & analytics are taught and/or applied for data driven innovation. Again, we have also used the evaluation results of the TUN Analytics Challenge as they represent a comprehensive sample of different universities and course settings (Dinter and Kollwitz 2016). The dimension *data value chain* refers to its key activities. By compiling previous work from Curry (2016), Hartmann et al. (2016), and Miller and Mork (2013) we have identified the following attributes which we could also find in various combinations in the TUN Analytics Challenge: *data generation, data acquisition, data processing, data aggregation, analytics*, and *visualization*. Furthermore, we have added two dimensions to the morphological box describing the applied analytics techniques in more detail. The established categorization of analytics types (dimension *analytics perspectives*) into *descriptive, predictive*, and *prescriptive* analytics (Davenport 2012) is in line with the analysis of the TUN Analytics Challenge as well as Chen et al.´s (2012) *analytics technologies* which we have adopted slightly to our context by including the attributes *(big) data analytics, text analytics, network analytics*, *streaming analytics and web analytics*.

Innovation Approach

This category addresses the innovation-related design options for the course. The dimension *innovation method* specifies if and which kind of innovation method (in the sense of a process model or a framework) is given. Examples for given methods *grounded in innovation management* literature are design thinking or innovation games (see Trifilova et al. 2016). Methods can also be *grounded in analytics*, for example in analytical frameworks such as the Cross Industry Standard Process for Data Mining model (CRISP-DM) (Shearer 2000). If no method is provided, the participants are in charge to choose an appropriate method or to structure the innovation process by themselves. The related dimension *creativity technique* (within the innovation process) differentiates between *intuitive* and *discursive* methods according to the common classification of Leenders et al. (2007). Intuitive techniques like brainstorming or the 635-method tend to be unstructured and aim at finding unconscious solutions, while discursive approaches like GMA or SCAMPER provide a structured framework for ideation and solution search. Moreover, some techniques combine elements of both types (e.g. Disney-method or Six-thinking-hats). With regard to the *ideation approach* two fundamentally different perspectives can be identified (Vanauer et al. 2015). The *business first* perspective starts with business requirements and aims at meeting those business questions by the means of available (big) data and analytics technologies. The *data first perspective* emphasizes the enabling role of big data & analytics. Therefore the ideation process is driven and inspired by available data and technologies and is open for new business models or use cases. Data driven innovation can be further taught on different *innovation levels*. On a *conceptual* level, the learners do not innovate with the data itself, but rather with scenarios or case studies in the domain of scope. They can also innovate and brainstorm on descriptions of data (so called *metadata*). In many cases, *data* will be investigated and analyzed aiming at identifying new use cases for it. Furthermore, the *data origin* can vary. The data can be accessed from *open data platforms* or might be provided directly by *companies*. In addition, it can be provided by the teacher of the course or it is self-generated by the students. Another dimension refers to the *tools* used in the course. These tools can be *given* by the teacher or can be *self-selected* by the students, depending on the availability, the use case and the main objectives of the course. The last dimension describes the *degree of elaboration*. We have adapted and streamlined the categorization of Bullinger and Möslein (2010) and distinguish between a *concept*, a *prototype* or a *full-fledged service*.

Morphological Box for Teaching Data Driven Innovation

Table 1 summarizes the findings of the morphological analysis by means of a morphological box.

Category	Dimension	Attributes						
Teaching Method	Knowledge	Factual	Conceptual	Procedural	Metacognitive			
	Cognitive processes	Remember-ing	Under-standing	Applying	Analyzing	Evaluating	Creating	
	Content presentation	Expository	Explorative					
	Knowledge acquisition	Cumulative	Cyclic					
Course setting	Level	Undergraduate	Master	MBA				
	Course format	Lecture	Tutorial	Workshop	Project	Hacka-thon	Innovation lab	Innovation contest
	Participation as	Individual	Team					
	Team composition	Monodisciplinary	Interdisciplinary					
	Third party involvement	Involved	No involved					
Course Content	Data value chain	Data generation	Data acquisition	Data pro-cessing	Data aggregation	Analytics	Visualization	
	Analytics perspective	Descriptive	Predictive	Prescriptive				
	Analytics technologies	(Big) data analytics	Text analytics	Network analytics	Streaming analytics	Web analytics		
Innovation Approach	Innovation method	Grounded in innovation mgt.	Grounded in analytics					
	Creativity technique	Intuitive	Discursive	Mixed				
	Ideation approach	Data first	Business first					
	Innovation level	Conceptual	Metadata	Data				
	Data origin	Open data	Company	Teacher	Self-generation			
	Tools	Given	Self-selected					
	Degree of elaboration	Concept	Prototype	Full-fledged service				

Table 1. Morphological Box for Teaching Data Driven Innovation

For better readability, the attribute "none" has been omitted for some dimensions, i.e. none of the attributes in this dimension applies in a certain teaching setting. For example, it is possible that the data driven innovation course doesn´t follow a specific innovation method or creativity technique.

Teaching Cases

Next, two examples of teaching cases are presented, in which we were able to gain experiences in teaching data driven innovation. The cases represent and illustrate different shapes of the morphological box and serve also for the evaluation of the artifact.

Case A: Data Driven Value Generation for the Internet of Things

This case consists of a course on data driven value generation for the internet of things develop by a task force at the institute of information systems of Friedrich-Alexander-University at Erlangen-Nuremberg. The course is directed at graduate students and executives (entrepreneurs and industry practitioners) with basic knowledge on digital data processing applications. It uses a pragmatic teaching approach based on Dewey and Kerschensteiner (Bredo 1994; Winch 2006), which addresses the whole scope of cognitive processes in problem solving, focussing on conceptual, procedural and metacognitive knowledge. The content presentation follows an explorative scheme; students have to work actively to uncover and identify relevant knowledge from practice. The knowledge acquisition works cumulatively. The course is held in a workshop setting with teams, usually from different disciplines. Learning proceeds by active participation in groups of 4-8 people who solve their own design problems, which allows them to pick different data analytics perspectives and technologies. Usually, different steps of the data value chain are considered together. The course draws on existing work in innovation management. During their work, the members of the groups use mixed techniques to get acquainted with analytical methods to understand the problem situation, different solution strategies and selection criteria, design methods and their application (see Stickdorn and Schneider 2011). Data are self-selected by the participants from any source(s) available to them or generated as test data. At the end of the workshop, the groups engage in a competition with each other for the best design solution, which allows an evaluation of their learning progress and forces them as well to start thinking about their work comparatively with respect of its value. Solutions are elaborated as prototypes. Depending on the number of participants and the depth in which the subject matter is explored, the workshops can last between half a day and four days.

The teaching format has already been applied several times in Germany, Tunisia, Taiwan, and Australia. Data from the competitions held in the end and further feedback collected orally and in written form implies that the setting can systematically support the acquisition of higher-level skills up to meta-cognition at the pragmatic end of Bloom’s taxonomy. Although the focus is set on other types of knowledge, factual knowledge also evolves during the workshop, as the participants are encouraged to use the internet to gain further background information on the problem situation or the internet of things in general. In line with the discourse on innovation education, we found that the tasks given to the participants have to be adequate to their background. Students need more support and information than experienced practitioners who have more knowledge and know how to expand it on their own with online sources and systematic questions to colleagues and teachers. It is also important to reflect on the progress and the learnings during the workshop repetitively, in particular to support an abstraction of the problem solving skills from the design solution developed in the workshop to generalized knowledge about value generation in the context of the internet of things.

Case B: Data Driven Innovation Project in the Field of E-mobility

This case describes a student project which was carried out in the winter term 2016/17 at Chemnitz University of Technology. It is embedded in the joint research project CODIFeY- Community based Service Innovation for e-Mobility, which is funded by the German Federal Ministry of Education and Research. Two teams with three students each from a BA & BI master program constituted a monodisciplinary team composition. In accordance with the objectives of the CODIFeY project, the students got the task to develop a concept as well as a prototype of a data driven service in the field of electronic mobility (e-mobility). The project was carried out over a whole semester term and during this period a kick-off-workshop, several meetings and a final presentation took place. Besides the development of a prototype, the teams had to write a detailed project report describing and reflecting their activities and decisions during the project. With regards to the applied teaching method the students were extensively engaged with the subject of data driven innovation during the project and thereby gained profound knowledge in creating innovative outcomes on a procedural and metacognitive level.

In the project, the students were guided by a slightly adapted CRISP-DM model and went through the stages (1) ideation and business understanding, (2) conceptualization and data understanding, (3) data modelling and prototyping and (4) presentation of results. This approach corresponds to an innovative method grounded in the analytics domain. Since the complete CRISP-DM process was carried out in the project all steps of the data value chain were addressed. In order to support the (1) ideation process and to stimulate creativity, a kick-off workshop with both teams was conducted and guided by a supervisor. Using an intuitive creativity technique, the students were collecting a variety of ideas as well as challenges of data driven innovation for e-mobility in a group-based brain writing process. Since problems and challenges of e-mobility in Germany have been collected and discussed firstly, the ideation approach can be classified as business first. In stage (2), both teams used the workshop results to create basic service concepts and set up a project plan. In this context, the teams also identified the data required for prototyping. To this end, the teacher provided a list of pre-selected and e-mobility related open data sources. Additional data sets had to be self-selected by the teams. In stage (3) the students collected and pro-processed the data and applied various analytics tools – without any specifications about the tools and analytics perspective from the teacher. In the final stage (4) the teams presented the prototypes.

A major advantage of this case is the complete execution of a data driven innovation cycle, from ideation to prototyping. Hence, besides analytics skills, process-oriented thinking, project management capabilities, creativity and teamwork are nurtured. Students learn from exploration of the subject matter on their own. In returning to the same teaching topics during the different phases of development, the knowledge acquisition is organized cyclically. In addition, working in separate groups allows the students to learn from each other, but, at the same time, adds a certain degree of competition to the class room. However, at some stages (in particular ideation and business understanding) cross-group work has proved to be successful. Disadvantages lie in the high effort to organize and carry out such a student project. Therefore, the format is difficult to apply to a large number of students.

Conclusion

In the paper at hand we have designed a morphological box for teaching data driven innovation and presented two examples for teaching cases which we have applied in class. We have combined findings from analyzing a series of academic analytics contests with existing literature. As we have shown, there is no gold standard for teaching data driven innovation in higher education, but rather many different options to do it. From the point of view of innovation research, this paper provides cases in the context of the digital transformation, which can be expected to gain further importance in upcoming years. Scholars and organizational decision makers are informed about the state of the art in course and program design for innovation teaching and gain an overview of the different design options available. From the point of view of big data research, the paper adds valuable insights about current practices of teaching in the field and a possible framework for their categorization and analysis.

Since our empirical analysis has referred to submissions of one single course format (innovation contest), the generality of our results is limited. The evaluation of the morphological box by means of the application of various teaching cases has started but has not yet been completed. For further research, we plan to analyze not only our own teaching cases but also to classify other cases according to the morphological box. In addition, the artifact will be discussed and refined with experts from the fields of innovation management and big data research on scientific conferences. Using the revised artifact as a foundation, we further aim at exploring which teaching settings and innovation approaches are particularly suitable for achieving specific learning objectives

References

Anslow, C., Brosz, J., Maurer, F., and Boyes, M. 2016. "Datathons: An Experience Report of Data Hackathons for Data Science Education," in *Proceedings of the ACM Technical Symposium on Computer Science Education (SIGCSE)*, Memphis, pp. 615–620.

Bloom, B. S. 1956. *Taxonomy of educational objectives: Handbook 1: Cognitive domain*, New York: David McKay.

Bredo, E. 1994. "Reconstructing educational psychology: Situated cognition and Deweyian pragmatism," *Educational Psychologist*, (29:1), pp. 23–35.

Bullinger, A. C., and Möslein, K. M. 2010. "Innovation Contests – Where are we?," in *Proceedings of Americas Conference on Information Systems Proceedings (AMCIS)*, Lima.

Cegielski, C. G., and Jones-Farmer, L. A. 2016. "Knowledge, Skills, and Abilities for Entry-Level Business Analytics Positions: A Multi-Method Study," *Decision Sciences Journal of Innovative Education*, (14:1), pp. 91–118.

Chen, H., Chiang, R. H. L., and Storey, V. C. 2012. "Business Intelligence and Analytics: From Big Data To Big Impact," *MIS Quarterly*, (36:4), pp. 1165–1188.

Collins, A., Brown, J. S., and Holum, A. 1991. "Cognitive apprenticeship: making thinking visible," *American Educator*, (15:3), pp. 6–11.

Couger, B. J. D., Higgins, L. F., and Scott, C. 1993. "(Un) Structured Creativity in information Systems Organizations," *MIS Quarterly*, (17:4), pp. 375–397.

Curry, E. 2016. "The Big Data Value Chain: Definitions, Concepts, and Theoretical Approaches," in *New Horizons for a Data-Driven Economy*, J. M. Cavanillas, E. Curry, and W. Wahlster (eds.), Berlin: Springer, pp. 29–37.

Davenport, T. H. 2012. *Enterprise Analytics: Optimize Performance, Process, and Decisions Through Big Data*, Upper Saddle River: Pearson.

Davenport, T. H., and Patil, D. J. 2012. "Data Scientist: The Sexiest Job of the 21st Century," *Harvard Business Reviewess Review*, pp. 70–76.

Debortoli, S., Müller, O., and vom Brocke, J. 2014. "Comparing business intelligence and big data skills: A text mining study using job advertisements," *Business and Information Systems Engineering*, (6:5), pp. 289–300.

Deng, X. N., Li, Y., and Galliers, R. D. 2016. "Business Analytics Education: A Latent Semantic Analysis of Skills , Knowledge and Abilities Required for Business versus Non- Business Graduates," in *Proceedings of the International Conference on Information Systems (ICIS)*, Dublin, pp. 1–14.

Dinter, B., and Kollwitz, C. 2016. "Towards a Framework for Open Data Related Innovation Contests," in *2016 Pre-ICIS SIGDSA/IFIP WG8.3 Symposium*, Dublin, Ireland, pp. 1–9.

Fichman, R. G., Dos Santos, B. L., and Zheng, Z. E. 2014. "Digital Innovation as a Fundamental and Powerful Concept in the Information Systems Curriculum," *MIS Quarterly*, (38:2), pp. 329–353.

Fritzsche, A., and Oks, S. J. 2016. "Learning to speak 'digital' – how industry applies cyber-physical design concepts in new systems implementations," in *Information Systems Foundations Workshop: Theorising Digital Innovation*, Canberra.

Gupta, B., Goul, M., and Dinter, B. 2015. "Business intelligence and big data in higher education: Status of a multi-year model curriculum development effort for business school undergraduates, MS graduates, and MBAs," *Communications of the Association for Information Systems*, (36:1), pp. 449–476.

Guthrie, C. 2014. "Empowering the hacker in us: a comparison of fab lab and hackerspace ecosystems," in *5th Latin American and European Meeting on Organization Studies*, Havana, pp. 1–18.

Halverson, E. R., and Sheridan, K. M. 2014. "The Maker Movement in Education," *Harvard Educational Review*, (84:4), pp. 495–504.

Hartmann, P. M., Zaki, M., Feldmann, N., and Neely, A. 2016. "Capturing value from big data – a taxonomy of data-driven business models used by start-up firms," *International Journal of Operations & Production Management*, (36:10), pp. 1382–1406.

Krathwohl, D. R. 2002. "A Revision of Bloom's Taxonomy: An Overview," *Theory into Practice*, (41:4), pp. 212–264.

Leenders, R. T., van Engelen, J. M. L., and Kratzer, J. 2007. "Systematic Design Methods and the Creative Performance of New Product Teams: Do They Contradict or Complement Each Other?," *Journal of Product Innovation Management*, (24:2), pp. 166–179.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., and Byers, A. H. 2011. "Big data: The next frontier for innovation, competition, and productivity," *McKinsey Global Institute*.

Marjanovic, O. 2012. "Using the Revised Bloom'S Taxonomy To Scaffold Student Learning in Business Intelligence/Business Analytics," in *Proceedings of the European Conference on Information Systems (ECIS)*, Barcelona, Spain.

Miller, H. G., and Mork, P. 2013. "From data to decisions: A value chain for big data," *IT Professional*, (15:1), pp. 57–59.

Provost, F., and Fawcett, T. 2013. "Data Science and its Relationship to Big Data and Data-Driven Decision Making," *Data Science and Big Data*, (1:1), pp. 51–59.

Ritchey, T. 2011. *Wicked problems–social messes: Decision support modelling with morphological analysis*, Berlin: Springer.

Schön, S., and Ebner, M. 2014. "The Maker Movement. Implications of new digital gadgets, fabrication tools and spaces for creative learning and teaching," *eLearning Papers*, (39), pp. 86–100.

Shearer, C. 2000. "The CRISP-DM Model: The New Blueprint for Data Mining," *Journal of Data Warehousing*, (5), pp. 13–22.

Stickdorn, M., and Schneider, J. 2011. *This is service design thinking: Basics, tools, cases*, Hoboken: Wiley.

Topi, H., Karsten, H., Brown, S. A., Carvalho, J. A., Donnellan, B., Shen, J., Tan, B. C. Y., and Thouin, M. F. 2017. "MSIS 2016: Global Competency Model for Graduate Degree Programs in Information Systems," *Communications of the Association for Information Systems*, (forthcoming).

Trifilova, A., Bessant, J., and Alexander, A. 2016. "Q&A: How Can You Teach Innovation and Entrepreneurship?," *Technology Innovation Management Review*, (6:10), pp. 45–50.

Vanauer, M., Bohle, C., and Hellingrath, B. 2015. "Guiding the introduction of big data in organizations: A methodology with business- and data-driven ideation and enterprise architecture management-based implementation," in *Proceedings of the Annual Hawaii International Conference on System Sciences (HICSS)*, Kauai, pp. 908–917.

Wang, Y. 2015. "Business Intelligence and Analytics Education: Hermeneutic Literature Review and Future Directions in IS Education," in *Proceedings of Americas Conference on Information Systems Proceedings (AMCIS)*, Puerto Rico, pp. 1–10.

Winch, C. 2006. "Georg Kerschensteiner—founding the dual system in Germany," *Oxford Review of Education*, (32:3), pp. 381–396.

Wixom, B., Ariyachandra, T., Douglas, D., Goul, M., Gupta, B., Iyer, L., Kulkarni, U., Mooney, J. G., Phillips-Wren, G., and Turetken, O. 2014. "The current state of Business Intelligence in academia: The Arrival of Big Data," *Communications of the Association for Information Systems*, (34:1), pp. 1–13.

Zolnowski, A., Christiansen, T., and Gudat, J. 2016. "Business Model Transformation Patterns of Data-Driven Innovations," in *Proceedings of the European Conference on Information Systems (ECIS)*, Istanbul.

Zwicky, F. 1969. *Discovery, invention, research through the morphological approach*, New York: MacMillian.