Towards a Design Model for Interdisciplinary Information Systems Curriculum Development, as Exemplified by Big Data Analytics Education

Abstract

The need for interdisciplinary programs for problem-based education increases. However, there is a substantial shortage of skilled boundary-spanning students, as prominently evidenced in the field of big data analytics. To solve this problem, this paper suggests a generic interdisciplinary IS curriculum process design model. The model considers education of students with deep knowledge in more than one discipline who possess the right skills that are needed by their future employers. It is applicable to various disciplines and potential combinations of these disciplines. Based on skills representing the consensus of corresponding communities and professionals, the model allows the definition of university specific constraints which are considered in the curriculum design. Besides the process design model we have implemented a prototype for a curriculum generator which supports the generation of concrete curricula. Through our approach that is based on the design science research paradigm, we formalize the curriculum development process which allows the fast and easy design of interdisciplinary programs.

Keywords: Interdisciplinarity, Education, Design Science, Curriculum Design, Interdisciplinary Curricula, Model, Information Systems, Data Scientist, Analytics, Big Data.

1 Problem Statement and Motivation

In recent years, the demand for interdisciplinary university programs with problem-based curricula has been increasing. The field of information systems (IS) bears witness of this development through its successful combination of computer science and business studies (rendering itself an interdiscipline; Newell, 1983). A current trend that is expected to boost the need for interdisciplinarily trained students...
is big data. Big data not only is a hot topic, it is interdisciplinary by nature. The potential of quickly analyzing large amounts of data from diverse sources is acknowledged by many disciplines, including marketing (Davenport, et al., 2012), biology (Howe, et al., 2008), or the life sciences (Schadt, et al., 2010). A number of universities in North America and Europe have begun to develop Master of Science (MSc) programs in Data Science or Business Analytics. The development of such interdisciplinary curricula poses some challenges. Indeed, a closer examination reveals that big data analytics (BDA) programs are characterized by a considerable amount of heterogeneity, while their level of interdisciplinarity is modest at best. Starting from this perspective, we target to develop a general curriculum design model capable of generating interdisciplinary IS curricula. To illustrate the potential of our design model, we will build a prototype BDA curriculum generator.

Our solution contributes to the field of IS in at least two ways. First, the curriculum generator can help universities to develop BDA programs aiming at reducing the shortage of skilled data analysts (Chen, et al., 2012; Davenport, et al., 2012; Donovan, 2008). According to the McKinsey Global Institute Report (Manyika, et al., 2011), in the next five years the US alone will need 140,000 to 190,000 people with deep analytical skills within several knowledge domains. Second, we offer a generalizable account of interdisciplinary IS curriculum development that can be applied to most universities and study programs. Drawing on design science (Peffers, et al., 2007), we create a curriculum design model. It entails the artifacts and actors necessary to construct a curriculum. Hence, it formalizes the curriculum development process and offers guidance. At the same time, it does not prescribe which content is included but leaves room for universities to decide which application disciplines (e.g., biology, marketing) should be related with education of a particular core discipline (e.g., big data analytics). This information will generate a curriculum suited to meet the needs of the respective scientific community (e.g., education of skilled big data analysts specialized in biology, marketing, life sciences, etc.), but tailored to the respective university. We will use existing research findings to structure the artifacts and processes in our curriculum design model. Our approach guarantees that the resulting curricula are methodologically sound and, at the same time, flexible enough to be used by many universities worldwide.

The remainder of the paper is organized as follows: After a short presentation of the state of the art of IS curriculum development and existing models for IS curricula we discuss the need for new curricula in this field which cannot be modeled by using former approaches.

2 State of the Art of IS Curriculum Development

For theoretical foundation, we investigated the current state of IS curriculum development as well as existing models for IS curricula. In addition, we point out the demand for big data analysts resulting in a need for new curricula in this field which cannot be modeled by using former approaches.

2.1 Challenges of Curriculum Development

Research on curriculum development principles seems to be a well-established field. From early publications on general principles (e.g., Tyler, 1949) up to specialized models for specific domains (e.g., Noll & Wilkins, 2002), there is a wide range of guidelines and frameworks to support curriculum development. Multiple approaches highlight the importance of outcome-based curriculum design, such as Constructive Alignment (Biggs & Tang, 2007) or the Understanding by Design framework (Wiggins & Mc Tighe, 2005). The approaches suggest that selection of topic content as well as forms of assessment should follow the intended learning outcome quantity and quality. Implementing these
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models is still challenging (Noll & Wilkins, 2002) and there are only few established approaches available.

Looking at IS curricula in particular, a number of IS model curricula have been developed in the last decades, such as IS’95 (Couger, et al., 1995), IS’97 (Davis, et al., 1996), IS 2002 (Gorgone, et al., 2002) and IS 2010 (Topi, et al., 2010). In addition to these undergraduate programs, a Master of Science in IS (MSIS) has been proposed (Gorgone, et al., 2006). To guide the design of IS curriculum, we refer to the nine principles of the most recent curriculum, the IS 2010 (Topi, et al., 2010, p. 368): (1): representatively for the viewpoint of several stakeholders, (2) effectiveness, (3) adaptability to institutions, (4) recommending and supporting several pedagogical approaches, (5) adaptability to IS programs, (6) flexibility towards domains, (7) internationally acceptance of core contents, (8) complemented by elective content, and (9) no restrictions for pedagogy.

With regard to the demands of new curricula, such as BDA curricula, two major shortcomings can be identified in previous literature. In most cases, concrete curricula as well as contributions about curriculum development in general focus on a single domain or discipline. In the case of interdisciplinary curricula (which for sure already exist), little information is available if and how systematically such a curriculum has been developed. In addition, we see certain limitations in flexible curriculum design in terms of considering university specific constraints and contingency factors.

2.2 Requirements for Big Data Analytics Education

As already mentioned in the Introduction, the profiles of big data analysts and data scientists are characterized by explicit and extensive interdisciplinarity. So far, there is no broad consensus about a differentiation between big data analysts and data scientists, although some authors (e.g., Patil, 2011) regard the profile of a data scientist as broader. As both profiles share fundamental characteristics, in particular the interdisciplinarity and the need of interpersonal skills, we decided to include the data science profile in our literature review and in the exemplary development of a curriculum for big data analysts as well.

The profile of and the need for data scientists has recently attracted widespread attention, significantly initiated by Davenport et al. (2012). Davenport et al. and other authors (e.g., Chen, et al., 2012; Chiang, et al., 2012; Patil, 2011) emphasize the interdisciplinary nature of data scientist and big data analyst profiles, in doing so some authors mainly focus on the business application domain. Many papers refer to the Data Science Venn Diagram (Conway, 2010) which was a first attempt to illustrate the different skill areas a data scientist shall cover. Although differing slightly in detail, there seems to be a consensus that the following skill areas are needed for those profiles (Chen, et al., 2012; Chiang, et al., 2012; Conway, 2010; Davenport, et al., 2012; Laney & Kart, 2012; Patil, 2011): analytical skills, IT and programming skills, business and domain knowledge, and interpersonal skills (such as communication and curiosity). However, existing literature does not include any guidance how appropriate harmonized interdisciplinary curricula shall be developed.

In addition, recent contributions (such as Chen, et al., 2012; Chiang, et al., 2012; Laney & Kart, 2012; Thibodeau, 2012) suggest how the education of big data analysts and data scientists should look like and/or give an overview of current or future programs for these subjects. Finally, some authors discuss the question which disciplines should be or are already in charge of data science and big data education (EMC, 2011; Topi, 2013).
3 Development of an Interdisciplinary Curriculum Process Design Model

The increasing need for interdisciplinary IS curricula and for corresponding support for faculty has been elaborated in sections 1 and 2. Aiming at developing an interdisciplinary curriculum process design model we followed the design science research (DSR) process as introduced by Peffers et al. (2007). DSR is particularly suited for our problem as it specifically addresses the construction of socio-technical models for the IS domain (Gregor & Hevner, 2013). In so doing, it enables us to formalize the curriculum development process. The DSR process consists of six stages, namely (i) Problem Identification and Motivation, (ii) Objectives of the Solution, (iii) Design and Development, (iv) Demonstration, (v) Evaluation, and (vi) Communication. We use these stages to organize the remainder of this section. Stage (i) has already been addressed in the Introduction; hence, the subsequent discussion focuses on the remaining stages, starting with the definition of objectives.

3.1 Objectives of an Interdisciplinary Curriculum Process Design Model

In Section 2.1 we have identified shortcomings of previous literature that motivate our research. In particular, we consider the following two issues as essential for the BDA curriculum design and for interdisciplinary curricula in general.

- **Interdisciplinarity:** Regarding the aforementioned specialization of IS students in business (cf. Section 2.1), a BDA curriculum should instead be open to include other knowledge domains. Many disciplines besides business studies, including biology and the life sciences, need to quickly analyze large amounts of data (Howe, et al., 2008; Schadt, et al., 2010; Topi, et al., 2010). Consequently, an interdisciplinary BDA program may consider specializations (e.g., minor subjects) in more than one domain.

- **Flexibility:** As described above, an interdisciplinary curriculum can be designed for a variety of programs, e.g. bachelor or master programs. Aiming at designing a generic curriculum design model for interdisciplinary fields, it will also be crucial to respect the general conditions determined by the institutions themselves (cf. Gorgone, et al., 2006).

Therefore, in contrast to existing approaches (e.g., IS 2010 by Topi, et al., 2010, or MSIS 2006 by Gorgone, et al., 2006, in the IS field) for the development of a curriculum within a discipline, our solution aims at formalizing the development process of interdisciplinary curricula. However, the objectives and principles of those previous curriculum development contributions apply to our solution as well. We refer to the principles of the most recent and popular IS curriculum development endeavor (Topi, et al., 2010) as introduced in Section 2.1.

The most important objective for us, again, is assuring a high degree of interdisciplinarity. That is, the curriculum process design model is expected to generate curricula that are truly interdisciplinary, represented by an adequate share of courses outside the core discipline. Accordingly, courses from diverse application disciplines need to be considered to a reasonable extent.

The second objective refers to the flexibility of the solution. Flexibility is ensured when universities can adapt curriculum development to their individual needs and strengths. For example, they should have the option to adapt a curriculum according to their view of what is appropriate and feasible. Moreover, faculty should decide about appropriate teaching formats, such as lectures, tutorials, or workshops as well as methods that effectively prepare students for the requirements of the labor market (e.g., internships). The flexibility objective is an extension of several IS principles (specifically, it reflects IS 2010 principles 3, 4, 5, 7, and 9).
The third objective is to maintain validity of the remaining IS 2010 principles. Specifically, the resulting curriculum should represent a consensus from the respective scientific community. Although such consensus is demanded by many initiatives (e.g., Gorgone, et al., 2006; Topi, et al., 2010), most curricula target specific (mostly North American) educational systems (Gorgone, et al., 2006). The perspective taken here is broader and seeks to include insights from many countries. In addition, university graduates often do not have all skills needed in the workplace. Interdisciplinary programs may be particularly prone to such shortcomings as they do not have a long history of curriculum development. We therefore pay particular attention to a curriculum that is directed towards teaching the skills needed in the workplace.

Accordingly, the solution should:

1. support the development of interdisciplinary curricula,
2. allow universities to adapt the curricula according to their needs and contingencies, and
3. follow the principles as introduced by Topi et al. (2010), in particular:
   3.1. represent a consensus from the involved scientific communities (IS 2010 principle 1),
   3.2. provide students with the knowledge and skills suited to workplace responsibilities (IS 2010 principles 2, 6, and 8).

### 3.2 Design and Development of the Design Model

This section discusses the design and development of the solution. The solution has been developed by an interdisciplinary team consisting of five researchers with backgrounds in IS, computer science, business analytics, education, and marketing. The design mainly builds on existing approaches to curriculum development. We adapted and extended the approaches to guarantee the consideration of interdisciplinarity. Moreover, we added parametrization in terms of environmental constraints.

As a result, we developed the following DSR artifacts which constitute the interdisciplinary curriculum process design model:

- a **process model** for the development of interdisciplinary curricula, connecting participants, artifacts and activities involved;
- a **data model** describing the information generated and/or used by activities of the process model, including the interdisciplinary curriculum;
- a **pseudocode description** of a curriculum generator, which uses the data models and environmental constraints as input and derives an interdisciplinary curriculum; and
- an **instantiation** by means of a prototype which demonstrates the feasibility of the process model and the curriculum generator.

While our approach is generalizable to most interdisciplinary IS curriculum developments, we will use a concrete example for illustration purposes. The example is an interdisciplinary BDA curriculum with one core and different application disciplines. BDA considers the several skill sets that have been described in Section 2 (i.e., technology, analytical thinking, interpersonal skills, and domain knowledge). Hence, the exemplary BDA curriculum shares many features with most IS curricula. The process model consists of three stages (i.e. community consensus, professional consensus, curriculum design) that are discussed next.
3.2.1 Finding a Research Community Consensus

As required by outcome-based curriculum design approaches (e.g., Biggs & Tang, 2007; Wiggins & Mc Tighe, 2005) the process starts with formulating the skills necessary for the core as well as for the application discipline(s). These skills represent a consensus of the respective scientific community. While the core discipline knowledge is part of every curriculum covering a broader field, the application discipline knowledge depends on each specialization. In our exemplary BDA curriculum, the core discipline knowledge entails interpersonal and (some basic) technology skills, in addition to data analysis skills. Examples would be presentation, database, and data mining skills. The application discipline knowledge refers to those disciplines (e.g., marketing, biology) that need experienced big data analysts. Examples include segmenting markets or molecular biology.

Using the Business Process Modeling Notation 2.0 (Object Management Group (OMG), 2011), Figure 1 illustrates how the respective scientific communities first find a consensus (list of discipline skills) and afterwards make it available (e.g., via their website). Ideally, many stakeholders of the communities (e.g., representatives of prominent associations in the field) are involved in this process. The Association of Computing Machinery (ACM) uses a similar approach, providing evidence that the communities are willing and able to find and afterwards publish a consensus1. However, if this is not possible for a specific discipline, a list of critical discipline skills can also be derived by the universities themselves. In the BDA example, representatives of major associations (e.g., Association for Information Systems, ACM, Society for Information Management, Decisions Sciences Institute, INFORMS-Information Systems Society, The Data Warehouse Institute, IEEE Computer Society) may regularly compile a list of skills necessary for big data analysts. Potential communities for major application disciplines would be the American Marketing Association, Academy of Management, American Medical Association, or Ecological Society of America.

![Figure 1: Process of Finding and Communicating a Consensus about Critical Discipline Skills](image)

3.2.2 Finding a Professional Consensus

In the second stage, discipline professionals evaluate the consensus skills according to workplace relevance. We suggest to use the MoSCoW prioritization (International Institute of Business Analysis (IIBA), 2009) to provide a ranking of discipline skills. The MoSCoW prioritization distinguishes between four groups of requirements which can be assigned to the following values:

- **Must:** Describes a skill that has to be part of the final curriculum.
- **Should:** Represents a high-priority skill that should be included in the curriculum if possible. This is often a critical skill, but one which can be satisfied in other ways if needed.

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1 [http://www.acm.org/education/curricula-recommendations](http://www.acm.org/education/curricula-recommendations)
• **Could**: Describes a skill which is considered desirable but not necessary. The skill will be included if time and resources permit.

• **Won’t**: Represents a skill that from a professional’s view is currently less relevant, but may be considered in the future.

As a result of this process, a **prioritized list of discipline skills** is created. Skills that are highly ranked tend to become core content, while skills at the lower end may be declared as elective content. In the context of our running example, professionals may label the skill ‘data mining’ as highly relevant (‘must’) and ‘IT infrastructure’ as nice to have (‘could’). The ranking might change over time, depending on how the labor market evolves. In IS, such evaluations have been reported on a regular basis (e.g., Harder & Harper, 2011; Lee, et al., 1995; Wu, et al., 2007).

Figure 2 summarizes this stage of the curriculum development process model and illustrates how the prioritized lists of discipline skills are published. Publishing can be executed either via the website of a professional association or within the scientific communities.

![Flowchart](image)

**Figure 2**: Process of Evaluating the Critical Discipline Skills and Communicating the Results

### 3.2.3 Designing the Curriculum

While stages 1 and 2 typically take place outside a specific university, the third stage involves both, the department in charge of the core discipline and the department(s) in charge of the application discipline(s). First, the departments link the ranked skills of their discipline with educational objectives. Building on the revised Bloom taxonomy (Krathwohl, 2002) that distinguishes six educational objectives (i.e., remember, understand, apply, analyze, evaluate, and create), every skill is assigned to an educational objective. These assignments will be conducted for undergraduate and for graduate levels. For example, an undergraduate may need application knowledge in the skill ‘data mining’ (educational objective ‘apply’), while a graduate needs a more advanced level (e.g., educational objective ‘evaluate’). In addition to the values defined by Krathwohl (2002), ‘not required’ is included to allow universities to dismiss some of the skills suggested in stages 1 and 2. The **core skill-educational objective combinations** (hereafter “core skill levels”) and the **application skill-educational objective combinations** (hereafter “application skill levels”) are intermediate results of this curriculum development process step and indicate to what degree a university deems a certain skill important.

In addition to the separate compilation and ranking of discipline skills, each application discipline can also impact the core skill levels. This is the case when a skill is more or less relevant for a specific discipline. For example, while business intelligence skills may be considered less important for the average BDA graduate, the marketing department could place high importance on that skill. In this case, the marketing department can claim a veto and change the educational objective of the business intelligence skill from, say, ‘not required’ to ‘analyze’, resulting in an **updated core skill level list**. The next step of stage 3 focuses on the **course database**. In this database, all courses are listed the
A university can offer for the interdisciplinary education, supplemented by information about the course type, course credits, and skill reference, which in turn denote the intended educational objectives (taught skill level), and educational objective prerequisites (demanded skill level).

As the final step within the third stage of the curriculum development process model, the curriculum generator creates a curriculum for specific application discipline(s), consisting of a graduate and an undergraduate curriculum. As input serve the created course database, the application skill levels, and the updated core skill levels, together with environmental constraints (e.g., as course credits). The strict formalization of the process allows the curriculum generator to automatically perform validation checks. If any invalid values are detected, a respective notification is generated by the system, guiding the user to make corrections; the user (university) either has to create a new course or needs to adapt the intended skill levels. For further details on the validation checks, we refer to the pseudocode description in Appendix A. Figure 3 summarizes the third stage of the development process model including the sequence flow in case of a validation exception (represented in light grey; starting in the lower-right corner).

Figure 3: Curriculum Design and Generation Process

The presented design stages with regard to the curriculum data model as introduced by Topi et al. (2010) lead to the following input and output data models for the curriculum generator. We use the UML 2.3 class diagram notation (OMG, 2010). Figure 4 depicts the generator’s input, showing the result of the MoSCoW prioritization in the upper and the university’s skill level lists in the lower area. The diagram is almost symmetrical, with core discipline data on the left and application discipline data on the right side. An exception was made to the updated core skill levels: here, the application discipline may define an updated educational objective overwriting the core discipline’s value for the required educational objective (lower left area in Figure 4).
Figure 4: Curriculum Generator Input Data Model (extended version based on Topi et al. 2010)

Figure 5 depicts the generator’s output whose main element is the curriculum that consists of the selected course list. Each course refers to a list of skills that are either required or taught, or both. Thus, each entry specifies the maximum demanded (i.e., preconditioned educational objective) and the taught educational objective for that skill, defining all educational objectives in-between as taught, too. For example, the course ‘Data Mining II’ may refer to the skill ‘data mining’ which is required in educational objective ‘apply’ and taught in ‘evaluate,’ implying that ‘analyze’ is taught as well. The highlighted area depicts the course database which has been specified by the university (see Figure 3) and of which the courses are selected.

Figure 5: Curriculum Generator Output Data Model

In the following, we explain the work flow of the curriculum generator. Since the explanation of the complete algorithm is beyond the scope of this paper, we present the pseudocode for the main routine (see Appendix A). The pseudocode is formatted using instructions from Zobel (1997) who suggests the use of prose over the use of programming language constructs and notation. Nonetheless, we use Boolean predicates to represent assertions. Note that lower-case letters represent singular entities: \( c \) is a course, \( s \) is a skill, and \( o \) is an educational objective.
The main routine generates a curriculum for a specified graduation level, and, therefore, is utilized by a surrounding routine that generates the curriculum for both, undergraduate and graduate programs. Validation of curriculum size is also performed in the surrounding routine. Additionally to the validation of the maximum-credit-constraint, a validation regarding the ‘overachievement’ of a specific course is performed. A course is qualified as ‘overachieved’ if it reached a higher educational objective within a curriculum than required. However, the GenerateCurriculum function computes the best set of courses which fulfill the required educational objectives for a certain graduation level. The definition of “best” is realized by means of a performance function and, thus, may be replaced depending on the usage scenario. It allows the specification of skill levels which are already fulfilled by a student before entering this curriculum in terms of a professional qualification.

3.3 Demonstration of the Design Model’s Feasibility through Instantiation

In order to demonstrate the feasibility of our curriculum design model we implemented an HTML and JavaScript based prototype which can be accessed via http://www.interdisciplinary-curriculum-development.com. The prototype also contains additional information on each step described below.

To be able to simulate different scenarios we prepared a set of consensus skills for the core discipline BDA as well as different sets of census skills for two application disciplines: marketing and biology/bioinformatics. Accordingly, the following scenarios can be simulated:

1. the development of an interdisciplinary big data analytics/marketing curriculum and
2. the development of an interdisciplinary big data analytics/bioinformatics curriculum.

We derived the set of consensus skills for the core discipline from published lists (e.g., Chiang, et al., 2012; Lee, et al., 2002; Lee, et al., 1995) as well as through careful study of more than 25 data science or (business) analytics curricula. The marketing skill set was taken from Walker et al. (2009). The biology and bioinformatics skill set is based on work by Gibas & Jambeck (2001) as well as the selection of approved elective biology and bioinformatics courses for New York University’s extensive Data Science program. The interdisciplinary research team (with backgrounds in IS, computer science, business analytics, education, and marketing) evaluated all materials and prioritized respective skills. All inconsistencies were resolved through discussion. Although the resulting lists only serve for illustrational purposes, they nonetheless display a fairly realistic account of the requirements for students in the respective field.

To minimize the required user input we further prepared the prioritized list of skills for all domains (in real-world applications, this step should be conducted by discipline professionals), the lists of discipline skill levels (which would be conducted by the department in charge), the updated core skill levels list (which would be conducted by the department in charge of application discipline), and an exemplary course database (based on the courses offered by 25 of the leading data science/analytics programs; in real-world applications conducted by the departments in charge).

All generator input variables, namely the updated core skill levels list, the application skill levels list, the exemplary course database as well as environmental constraints can be changed. The changes can result in one of the following cases:

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the curriculum generation fails because not all educational objectives can be achieved for each skill (either the course database does not provide adequate courses or the educational objectives within the skill levels lists are too demanding).

the curriculum generation fails because the appropriate curriculum contravenes the environmental constraints (e.g., the provided maximum amount of credits is too small), or

the curriculum generation is successful and an adequate curriculum is generated and presented.

In the failure cases, the prototype provides information on the reasons causing the failure. The information can be used to adapt the course database, the updated core skill levels list, the application skill levels list, or the environmental constraints. After completion, a new generation process can be initiated. Hence, the prototype guides the user to develop an adequate curriculum. Figure 7 shows an exemplary generated big data analytics/marketing curriculum using the prototype. Please note the remark ‘Overachievement’ in the right area of Figure 7, e.g. for the skill ‘Basic Statistical Analysis’.

As an additional option, the prototype provides the functionality to generate a bachelor curriculum only, a bachelor and a consecutive master curriculum, or a master curriculum only for both aforementioned scenarios.

3.4 Evaluation of the Design Model using a Real World Example

Again, following the DSR process as suggested by Peffers et al. (2007), we evaluate the interdisciplinary curriculum process design model in terms of the three defined objectives as described
in Section 3.1. First, it should be truly interdisciplinary. Second, the solution should be flexible. Third, it should follow the remaining IS 2010 principles, most notably regarding the consensus from the involved scientific communities as well as provision of the knowledge and skills suited to workplace responsibilities.

Regarding the first objective, the resulting curricula are comprised by balanced levels of both, the core and application discipline(s). Since no particular discipline dominates the curriculum content, objective 1 is met.

Second, the model guides but not prescribes. Because universities are still free to develop curricula according to their preferences and there are no prescriptions (only additional information and suggestions are presented which may help to make the right decision), this objective is met. In addition, the formalized development process allows automatic validation checks including the presentation of failure causes which guide the development towards an adequate curriculum as demonstrated by our prototype.

Third, it represents a consensus from the involved communities, because the communities are directly involved in the development model. However, if this is not the case for a specific discipline, our prototype demonstrates that it is possible to gain insights about the consensus by deriving skills from published skill lists, which represent a fairly realistic account of the requirements of students in the respective field. Moreover, the solution provides students with knowledge and skills suited to workplace responsibilities. Because discipline professionals are also directly involved in the development model, the third objective is met, too.

The prototype serves not only for demonstrational purpose. It is also used to evaluate our curriculum development model. In fact, we are using it to develop an interdisciplinary big data & analytics masters curriculum at Chemnitz University of Technology. Besides that, the prototype is available for public and has already been tested by other researchers with positive feedback. Therefore, we cautiously claim our developed model as success.

We are aware that further empirical evaluation methods would support our argumentation. Both expert interviews and case studies can serve for this purpose. With expert interviews the real world suitability of our solution can be discussed while case studies are suitable to evaluate the advantage of our formalized model in contrast to existing approaches. Possible metrics for the latter can be directly deduced from the established objectives (addressing the quality of our solution): percentage of covered consensus skills, percentage of workplace requirements met, and estimation of the ratio between guidance and prescription. In addition, further quantitative metrics are conceivable, for example time needed for curriculum development or amount of time to receive accreditation. The planning of these additional evaluation steps is in our current focus.

3.5 Communication of the Results

Communication of the results will take place mainly by means of research papers, starting with this contribution. In addition, our developed prototype contributes to the communication. After the outlined empirical evaluation it is planned to finalize the prototype and make it available to the IS community via one of the major IS communities, like the Association for Information Systems.

4 Conclusion and Further Work

The aim of the paper at hand was to create a design model for interdisciplinary IS curricula. The design model aims at filling the gap of experts in various fields, including big data analytics. The approach taken in this paper is to create a solution that is able to consider the process and established principles of IS curriculum development. A prototype of this solution demonstrates its usefulness in
generating interdisciplinary curricula that reflect the individual characteristics of universities. At the same time, our approach offers a high level of guidance due to consideration of a scientific community consensus with respect to the skills that should be taught. The prototype illustrates interdisciplinary IS curriculum development for big data analytics, with specializations in either marketing or biology and bioinformatics. Moreover, curricula for bachelor and/or master degrees can be generated. In summary, the prototype is a powerful tool that can assist universities in their curriculum development activities. The objectives of the solution as defined before have been met.

A key concern of our approach is to consider education of students who have the right skills that are needed by their future employers (including scientific organizations). This means that the solution is flexible to changes in the environment and, thus, differs from the static model curricula. Instead of complete model curriculum revisions on a regular basis, our design science-based solution can handle revisions both at the research community level as well as the university or department level. This means that its dynamic nature is, by design, future-proof. Of equal importance is the generator's ability to include many diverse core and application disciplines. The procedure described in the context of big data analytics education can easily be expanded to most if not all combinations of more than one discipline.

While this paper presents an important contribution for all faculty members involved with interdisciplinary curriculum development, further improvement is needed. For example, future versions of the curriculum generator could align course selection with suggestions about the optimal semester in which the course should be taught. This feature will help curriculum developers in balancing the workload for students. In addition, the benefits of the suggested curriculum model should be evaluated by a large and diverse expert panel. The feedback of these reviewers is needed to appropriately reflect the needs of many scientific communities and universities. Currently, the environmental constraints can only be added by means of parameters and the generator neglects additional practical constraints of interdisciplinary curriculum design. However, a future version of the generator may also handle university specific rules, like the maximum/minimum number of courses a specific department can offer.

References


Appendix A: Pseudocode of the Curriculum Generator

**Input:**
- $S$: array of all known skills.
- $provides(s, o)$: true if and only if skill $s$ is already taught in skill level $o$.
- $requires(s, o)$: true if and only if skill $s$ is required in skill level $o$ according to the application and updated core skill level lists. There must be no overlapping between $provides$ and $requires$.

Additionally, the course database provides two predicates:
1. $teaches(c, s, o)$: true if and only if course $c$ teaches skill $s$ in skill level $o$.
2. $demands(c, s, o)$: true if and only if course $c$ demands an education of skill $s$ in skill level $o$.

**Variables:**
- $Candidates$: array of courses which fulfill the current skill level.
- $owing(s, o)$: true if and only if the skill level $o$ of skill $s$ is still to be taught, i.e. required and not yet taught by a selected course.
- $taught(s, o)$: true if and only if the skill level $o$ of skill $s$ is taught by a hitherto selected course, i.e. a course in $Curriculum$.

**Output:**
- $Curriculum$: a set of courses which fulfill the required skill level.

**Variables:**
- $Candidates$: array of courses which fulfill the current skill level.
- $owing(s, o)$: true if and only if the skill level $o$ of skill $s$ is still to be taught, i.e. required and not yet taught by a selected course.
- $taught(s, o)$: true if and only if the skill level $o$ of skill $s$ is taught by a hitherto selected course, i.e. a course in $Curriculum$.

**Sequence of GenerateCurriculum:**

1. Initialize the local variable $owing(s, o)$ to include all required skills and skill levels:
   For each known skill $s$ in $S$,
   a. Set $owing(s, o) ← required(s, o)$.
2. Iterate until every requirement has been met:
   While $owing(s, o)$ is not empty,
   a. Set $s_{max} ←$ the most important skill, i.e. the skill $s$ with the highest $o$ in $owing(s, o)$.
   b. Find the list of suitable courses $Candidates$:
      Set $Candidates ←$ all courses in $Courses$ that contribute to teaching $s_{max}$ in the highest required educational objective.
   c. If $Candidates$ is empty, exit with failure “skill $s$ cannot be taught sufficiently”.
   d. Identify the most suitable course $c_{0}$:
      i. For each course $c$ in $Candidates$, gather performance data such as the total number of taught skill levels or the number of additional skills (i.e. skills that are not required in $required(s, o)$).
      ii. Set $c_{0} ←$ the course $c$ in $Candidates$ which performs best. We may choose between several weighting functions. At the moment, we select a course that demands the fewest additional skills.
   e. Update variables according to $c_{0}$’s required and taught skills:
      For each known skill $s$ in $S$,
      i. Set $owing(s, o) ← true$ if $demands(c_{0}, s, o)$ and not $taught(s, o)$.
      ii. Set $taught(s, o) ← true$ and $owing(s, o) ← false$ if $teaches(c_{0}, s, o)$.
   f. Add $c_{0}$ to $Curriculum$.
3. Since $owing(s, o)$ is empty, all requirements have been met:
   Return $Curriculum$. 