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## Competency analytics tool: Analyzing curriculum using course competencies

Swapna Gottipati<sup>1</sup>  · Venky Shankararaman<sup>1</sup>

**Abstract** The applications of learning outcomes and competency frameworks have brought better clarity to engineering programs in many universities. Several frameworks have been proposed to integrate outcomes and competencies into course design, delivery and assessment. However, in many cases, competencies are course-specific and their overall impact on the curriculum design is unknown. Such impact analysis is important for analysing, discovering gaps and improving the curriculum design. Unfortunately, manual analysis is a painstaking process due to large amounts of competencies across the curriculum. In this paper, we propose an automated method to analyse the competencies and discover their impact on the overall curriculum design. We provide a principled methodology for discovering the impact of courses' competencies using Bloom's Taxonomy, Dreyfus' model and the learning outcomes framework. We developed the Curriculum Analytics Tool (CAT) which generates the competency scores for the entire curriculum across two dimensions; Cognitive levels and Progression levels. We use the CAT to analyse the competencies of an undergraduate Information Systems Management core curriculum program. Using 14 courses and the corresponding 578 competencies, this paper shows how our method enables us to perform in-depth analysis on the curriculum by discovering the cognition and progression statistics. We further apply the tool for recommending competencies when launching new courses.

**Keywords** Competencies · Bloom's taxonomy · Curriculum analysis · Exploratory data analysis · Competency cube · Undergraduate information systems program

# 1 Introduction

Competency based education is an institutional process that moves education from focusing on what academics believe students need to know to what students need to know and be able to do in varying and complex situations (Feiman-Nemser 1990). Competency based learning requires faculty and academic leaders to focus on learning outcomes which are subsequently broken down into competencies along sequential levels of mastery. Learning outcomes and competencies are employed in numerous education programs for achieving transparency and clarity in course design and delivery (Baumgartner and Shankararaman 2013). They are not only beneficial to the teaching professionals for structuring the courses, but also for students to track their skills development.

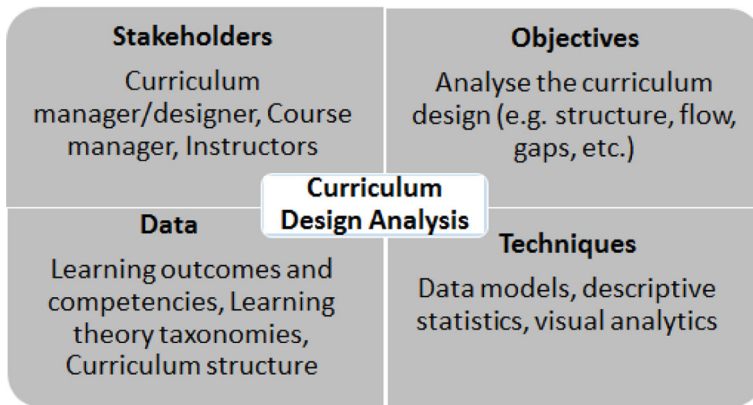
Curriculum analysis unpacks the components of a curriculum to assess and improve it. The curriculum level analysis of competencies has been studied by (Proli and Dondi 2011; Brabrand and Dahl 2009; Gnana Singh and Leavline 2013). Nevertheless, there was no principled approach or framework defined for in-depth analysis at the overall curriculum level across an entire program. Several researchers have proposed frameworks or methods to apply learning outcomes and competencies for evaluating the students (Scott 2003; Lister and Leaney 2003), and course design and delivery (Hartel and Foegeding 2004; Baumgartner and Shankararaman 2013; Shankararaman and Ducrot 2016; Ducrot et al. 2008; EU 2014). However, the major drawback of these studies is that, they mainly focus at the course level and in many cases the impact on the overall curriculum design is unknown.

Analysing competencies at curriculum level has several advantages. Firstly, it aids in understanding the overall design of the curriculum in terms of skills progression. It allows us to study the progression of skills from the first to the final year of the program. For example, if a course in the first year lays undue emphasis on advanced thinking skills, it can be moved to the advanced level. Secondly, it helps in discovering any discrepancies, blind spots or gaps in the program, and provides pointers for improving the curriculum. For example, if a particular skill is never addressed in the entire program, this becomes evident and appropriate action can be taken. Thirdly, it helps in recommending the competencies for a new course. For example, when introducing a new course, an analysis of competencies across existing courses will help in identifying the required competencies for the new course such that the overall progression of skills is well designed and aligned with program outcomes.

The conceptual framework of using competencies for analyzing curriculum design is depicted in the Fig. 1.

The four dimensions of the framework (Gottipati and Shankararaman 2014a) are:

- *Stakeholders*- “The targeted audience of the analysis.” Stakeholders are either the beneficiaries of the process or the suppliers of the data. The beneficiaries are meant to act upon the outcome of the analysis. In certain cases both the groups can be same.
- *Objectives*- “The purpose of the analysis.” The main objective of curriculum design analysis is to unveil the hidden information from the data related to the curriculum and aid the stakeholders in the curriculum design analysis. The newly discovered information as the output of the analysis will help in decision making. For example,



**Fig. 1** Curriculum design analysis conceptual framework (CDACF)

modifying the competencies for a specific course or re-organizing the flow the courses within the curriculum.

- *Data*- “The data that is gathered, and managed for conducting the analysis.” The data can be both specific to the curriculum, such as learning outcomes and competencies, flow of courses within the curriculum, or generic learning taxonomies and models such as Blooms cognitive models and Dreyfus progression models. Linking such datasets would facilitate the analysis, recommendation and prediction tasks related to curriculum design analysis.
- *Techniques*- “The techniques that are used in conducting the analysis.” A variety of data modelling and analysis techniques can be applied in the curriculum design analysis process. For example, data models, descriptive statistics, and visual analytics. Through these techniques one can generate tailored output to the stakeholders.

Manual curriculum design analysis using competencies can be a tedious and painstaking effort due to three main challenges. Firstly, even in a small curriculum, the total number of competencies can reach few hundreds. For example, in our dataset of 14 courses, we have 578 competencies in total. Secondly, the competencies are verbose in nature and often multiple competencies are combined into a single statement. For example, the competency statement, *Create and evaluate the business process model for a given real world scenario* consists of two competencies; *Create the business process model for a given real world scenario* and *Evaluate the business process model for a given real world scenario*. Thirdly, competencies tend to evolve, especially in technology curriculum where changes happen every two to three years. Hence, there is a need for an architecture for automating curriculum design analysis, and a tool that will implement the architecture, handles verbosity, generates statistics and analytics to aid the educationist in the decision making process.

From previous studies, we notice that in majority of cases, competencies are defined using Bloom’s taxonomy (Bloom et al. 1956). In particular, the cognitive domain of Bloom’s taxonomy has been very popular for exploiting the cognitive functionality of a course (Lister and Leaney 2003; Whetten 2007; Wheeler 2007). We also observe that a course is designed with the skill progression functionality, which focuses on the progression of a students’ skill levels from novice to expert (Dreyfus and Dreyfus 1986).

Therefore, inspired by these two observations our research is based on cognitive and progression functionalities. The competencies are studied under two dimensions; cognitive levels and progressive levels.

In this paper, we propose an Automated Curriculum Design Analysis Solution Architecture based on cube models (Khairuddin and Khairuddin 2008), Bloom's taxonomy (Bloom et al. 1956), Dreyfus' model of skill development (Dreyfus and Dreyfus 1986) and exploratory data analysis (EDA) (Cook and Swayne 2007) to discover the impacts of courses' competencies on the curriculum design. The solution architecture is divided into two phases; Alignment and Analysis. In the "Alignment Phase", the cube model integrates the learning outcomes (subsumes competencies), Bloom's cognitive domain (cognitive functionality) and Dreyfus' skill development stages (progression functionality) and produces the output of competencies aligned by cognition and progression (Gottipati and Shankararaman 2014b). In the "Analytics Phase", this output along with course information is analysed using EDA to produce the curriculum statistics. We developed the Curriculum Analytics Tool (CAT) that implements the solution architecture to map the competencies across the curriculum courses, along both the dimensions, cognitive and progression. We applied the tool to recommendation problem where for a given new set of course learning outcomes, the tool recommends the competencies along the cognitive level.

We evaluated Curriculum Analytics Tool (CAT) on an undergraduate core curriculum; Bachelor of Science (Information Systems) degree program BSc (IS), offered by the School of Information Systems (SIS), Singapore Management University (SMU). Our results show that the curriculum satisfies the different cognitive levels and progression levels. Additionally, it helped us in identifying some discrepancies in the curriculum design and then we proposed suggestions for improvements. Our major contributions from this work are as follows:

1. We studied a new problem of discovering the impact of courses' competencies on overall curriculum design in two-fold. First, by cognitive functionality and second, by progression functionality.
2. We proposed an Automated Curriculum Design Analysis Solution Architecture based on Bloom's taxonomy and Dreyfus' skill development model that integrates with learning outcomes to generate the competencies which are aligned cognitively and progressively. The solution architecture uses EDA for generating the statistics and insights on the curriculum.
3. We develop a Curriculum Analytics Tool (CAT), a desktop application, and present analysis of the curriculum by cognitive functionality as well as progression functionality. We evaluated the tool on an undergraduate core curriculum with 14 courses and 578 course competencies.
4. We evaluated our tool on recommendation problem. Our average recommendation score accuracy is 74.69% when tested on 14 courses.

The rest of the paper is organized as follows. In Section 2, we present related work on learning outcomes, competencies, design and analysis taxonomies, and education data mining in educational field. We give some background of Bloom's taxonomy and learning outcomes framework and discuss why they are relevant for our solution in Section 3. Section 4, presents our solution architecture and the Competency Analytics

Tool (CAT). In Section 5, we describe the extensions to our tool to include the recommendation feature. Section 6 presents the datasets used for the evaluation. Finally, in Section 7, we present the evaluation and analysis results of the tool. We also present threats to validation and we conclude in Section 8.

## 2 Literature review

### 2.1 Frameworks for learning outcomes and competencies

Learning outcomes are statements of a learning achievement and are expressed in terms of what the learner is expected to know, understand and be able to do on completion of the program (Kennedy 2007; Kennedy et al. 2009). The competency is usually expressed for individual courses within the curriculum, using the vocabulary of learning outcomes, i.e. express the required competence in terms of the students achieving specific educational programme learning outcomes (Kennedy et al. 2009). In response to the challenges of the twenty-first century, a considerable transformation of higher education is currently taking place. Instead of focusing on processes and inputs, the quality of higher education programs is being more and more assessed in terms of goals and outcomes – or, in other words, the learning outcomes are becoming accountability and quality assurance frameworks (Wheeler 2007).

The Qualification Frameworks (EU 2014), established through the EU Bologna process, are clearly based on learning outcomes and competencies and have become a central part of the European Higher Education.(Ducrot et al. 2008) defined a learning outcomes framework where the learning outcomes are at the program level and the sub skills (competencies) are specified under the learning outcomes. However, (Hartel and Foegeding 2004) defined a different relationship between competencies, objectives and learning outcomes. They defined competency as “a general statement detailing the desired knowledge and skills of students graduating from course or program” where by the competency is at a higher level than the learning outcomes.

In our paper, we adopt the definition of competency as defined by (Passow 2012): “Competencies are defined as the knowledge, skills and abilities in the context of a specific domain (object-oriented application development, cloud computing, etc.) that enable a student to take an effective action or make sound decisions”. Additionally, we use the learning outcomes framework defined by (Ducrot et al. 2008).

### 2.2 Learning taxonomies for design and analysis

Several learning taxonomies have been recognized as important paradigms in planning and developing educational, training, and professional development curricula (Bloom et al. 1956; Krathwohl 2002; O’Neill and Murphy 2010). The old Bloom’s taxonomy placed *evaluation* above *synthesis*. In contrast, the new Bloom’s version (Krathwohl 2002) has revised the terminology and placed *evaluation* below *create* level. Bloom proposed a simpler taxonomy for the cognitive domain, while Biggs’ SOLO taxonomy (O’Neill and Murphy 2010) is more complex and detailed framework. However, due to excellent structure of cognitive domain, Bloom’s taxonomy has been widely accepted in several education programs. To understand the progress

of skills learned, Dreyfus proposed a framework, skill development model (Dreyfus and Dreyfus 1986). The progression is from awareness to mastery and is perhaps more readily understood in relation to the progression of skill development from that of a beginner to an expert (Dreyfus and Dreyfus 1986). His model overlaps with Bloom's cognitive domain. For our solution, we used Bloom's taxonomy to analyse the curriculum on the cognitive functionality and Dreyfus' model of skill development for progression functionality.

Bloom's taxonomy has been applied in various aspects of learning and education; course design, structuring assessments, curriculum design, question generation, e-learning and distance learning projects. Scott described and tested categories in the cognitive domain as related to computer science assessments (Scott 2003). Using Bloom's cognitive domain, Lister and Leaney proposed method for assessing the students based on their ability (Lister and Leaney 2003). Using Bloom's taxonomy and learning frameworks, Whetten proposed the principles for effective course design (Whetten 2007). With the revised cognitive process, Wheeler studied the curriculum improvement problem (Wheeler 2007). Raykova et al. exploited the revised Blooms taxonomy for generating customized tests (Raykova et al. 2011). Bloom's taxonomy is integrated with learning outcomes in technology courses such as web application (Vignan et al. 2011) and software engineering (Proli and Dondi 2011). Similar to the above studies, in our paper, we applied Bloom's taxonomy for curriculum analysis. In particular, we applied Bloom's cognitive levels to course competencies to discover the impact of competencies on the overall curriculum design.

### **2.3 Educational data mining (EDM)**

Applying data mining techniques in education is an emerging research field and also known as educational data mining (EDM). It involves development of methods for making discoveries within the unique types of data from educational settings. The goal is to better understand students and the learning settings, and to gain insights of educational phenomena (Baker and Yacef 2009). In EDM, the most used techniques are exploratory data analysis (EDA), descriptive models, classification, clustering, Bayesian modelling, and relationship mining. Interpretation of results is an important step towards applying the knowledge discovered in the decision making process. In our solution, we applied EDA techniques (Cook and Swayne 2007), text mining algorithms and "Parts of Speech" taggers to process textual content of competencies.

Visualization techniques are very useful for showing results in a way that is easier to interpret. Visualization tasks include statistical modelling, regression modelling, information abstraction, mind maps, and usually data presentation in other forms like graphs, maps, and histograms. There are several studies oriented toward visualizing different educational data such as: patterns of annual, seasonal, daily and hourly user behaviour on online forums (Burr and Spennemann 2004); tutor-student interaction data from an automated reading tutor browsing through vast student instructor interactions to learn the student behaviour (Mostow et al. 2005); information visualized in e-learning using statistical graphs about assignments complement, questions admitted, exam score and so on (Shen et al. 2002); deficiencies in a student's basic understanding of individual concepts (Yoo et al. 2006); student tracking data regarding social, cognitive and behavioural aspects of students such as student attendance, access to

resources, overview of discussions and results on assignments and quizzes (Mazza and Milani 2004); visual environment for users to participate in the higher-education student evaluation data (Jin et al. 2009) and for mining and visualizing educational trails of web-pages visited and activities done (Romero et al. 2008).

### 3 Background

#### 3.1 Learning outcomes framework

Several frameworks have been proposed to integrate the learning outcomes into higher education (Hartel and Foegeding 2004; Ducrot et al. 2008; Shankararaman and Ducrot 2016). In Fig. 2, we show the Learning Outcomes Framework implemented at the School of Information Systems, Singapore Management University. The Learning Outcomes Framework (LOF) aims to shape the way the teaching professional designs and delivers the program courses, and at the same time the framework also aims to shape the student’s overall educational experience.

LOF consists of three major components: learning outcomes, competencies and assessments. While the learning outcomes have been established at the program level, competencies and assessment are defined at the individual course level. For each 1st level learning outcome, several 2nd level learning outcomes have been defined, and each 2nd level learning outcome has several competencies attached to it. In this framework, the learning outcomes are statements which are rather generic in nature, and those statements do not explicitly refer to any specific course or content covered in any particular course. Figure 3 shows sample competencies listed for the “Business Process Analysis and IT Solutioning” course in the undergraduate curriculum.

For example, some learning outcomes at the 1st level are, “Integration of business and technology in a sector context”, “IT architecture, design and development skills”, and “Project management skills”, etc. The corresponding 2nd level outcomes for “IT architecture, design and development skills” are, “Implementation skills”, “Software and IT architecture analysis and design skills”, etc. For the complete list of learning outcomes, please refer to (Baumgartner and Shankararaman 2013) and (Ducrot et al. 2008). The second important component of the learning outcomes framework is competencies. Contrary to the learning outcomes which are defined at the program-level (and are, thus, common for all core as well as elective program courses), the competencies are defined at the individual course level.

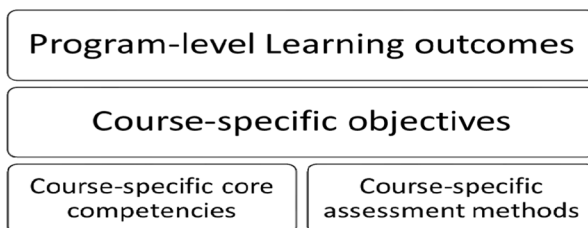


Fig. 2 Learning outcomes framework (program-level outcomes subsumes level 2 outcomes)



## 2. IT architecture, design and development skills

### 2.1. System requirements specification skills

**Competency 1:** Identify if a specific requirement is a business requirement or an IT requirement.

**Competency 2:** Identify if a specific IT requirement is functional or non-functional requirement.

**Competency 3:** Identify and extract business rules implicitly or explicitly used in existing business processes.

**Competency 4:** Create Organizational, Location, Collaboration and Workflow models for a given business scenario.

**Competency 5:** List most important models used to develop a Concept Solution Blueprint and identify their purpose.

**Competency 6:** List principle components of a Solution Blueprint and identify important requirements and inputs required to develop a Solution Blueprint.

**Competency 7:** Develop a Solution Overview and Application model using use cases and functions derived from the workflow model of a specific business process.

**Competency 8:** Select the most appropriate models and related information to be included in the Concept Solution Blueprint in a specific business scenario and justify the selection

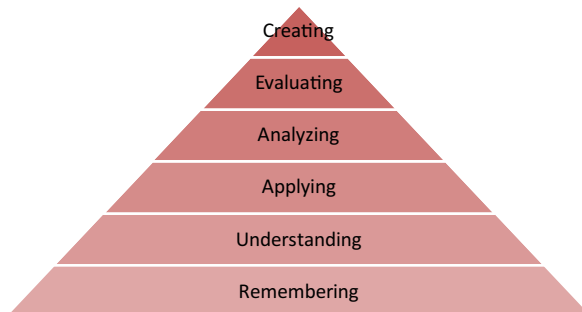
**Fig. 3** Competencies (an excerpt showing the learning outcome 2 with one of the associated 2nd level learning outcomes and the corresponding competencies for a second year course)

## 3.2 Learning taxonomies

Bloom's taxonomy divides the learning aspects into three domains; cognitive, affective and psychomotor. Cognitive domain focuses on the thinking level and has been widely applied in several domains including software engineering (Khairuddin and Khairuddin 2008) and engineering (Gnana Singh and Leavline 2013). Figure 4 depicts various levels in cognitive domain.

Bloom's cognitive domain involves knowledge and the development of intellectual skills. The first level of thinking is "*remembering*". In this level, the learner may have the ability to recall or remember facts without understanding them. The second level of thinking is "*understanding*". In this level, the learner may have the ability to understand and interpret learned information. The third level of thinking is "*applying*". In this level, the learner may have the ability to use learned material in new situations. The fourth level of thinking is "*analyzing*". In this level, the learner may have the ability to break down information into its components. The fifth level of thinking is "*evaluating*". In this level, the learner may have the ability to judge the value of a material for a given purpose. The sixth level of thinking is "*creating*". In this level, the learner may have the ability to put parts together. The lower three levels in the pyramid are also referred to as lower order thinking skills, and higher three levels are referred to as higher order thinking skills.

In addition to having standard method to facilitate course design and assessment on the cognitive scale, understanding the progressive stages for learning and skill development by individual learners is also important. The skill progression model identifies the different stages from novice to expert. Though there are two versions for the model



**Fig. 4** Bloom's taxonomy for cognitive domain (new version)

with five and six stages respectively, the three main stages play major role in tracking the progress of the learners; awareness, proficiency and mastery (Judith et al. 2008). A learner progresses from incompetent state to *awareness* wherein, the individual becomes aware of the skills lacking and gains an understanding of improving the skill. The learner then advances to a *proficiency* stage, wherein the learner is now demonstrating the knowledge needed and can perform reliably. Finally, the learner reaches the *mastery* stage, wherein the learner is now performing the skill as a second nature or intuitively.

To discover the impact of competencies on a curriculum, we propose a method which integrates all three components; the learning outcomes, cognitive taxonomy and skill progression model. The integrated model generates competencies which are aligned by cognitive as well as skill progression levels. Details of our solution method are explained in the next section.

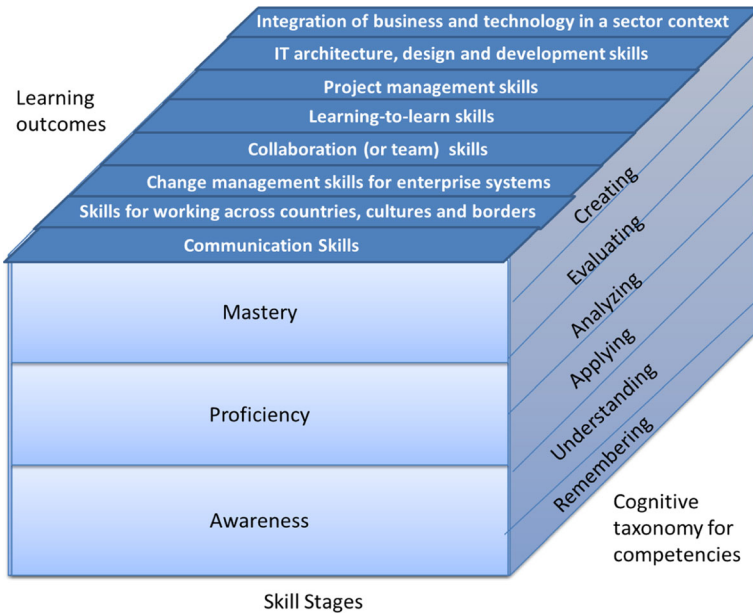
## 4 Solution method

In this section, we describe our method to discover the impact of competencies on the curriculum design. We first describe the competency cube, an integrated model, that can be sliced-and-diced to generate the outputs such as; competencies aligned by cognitive levels and competencies aligned by skill progression level. We then describe the automated curriculum analysis solution architecture and Competency Analytics Tool (CAT) that implements this architecture, which exploits the competency cube for each course, together with the exploratory data analysis (Cook and Swayne 2007) to produce curriculum statistics for the educationists.

### 4.1 Competency cube

A competency cube is a conceptual integrated model that supports the thinking about competency development. It was used by (Rodolfa et al. 2005) to frame the essential elements in the development of a professional psychologist, namely, the domains of functional competency, the domains of foundational competency and the developmental context in which the domains of competency are developed. We adopt this model to our context, by developing a cube that consists of three components; learning outcomes (subsumes the competencies), cognitive levels, and skill progression levels. We integrated all these three essential components as shown in Fig. 5. Each of the learning outcomes, as depicted on the z-axis of the cube, can be classified in relation to the level of cognitive functioning (see Fig. 5, y-axis) as well as each learning outcome can be classified to the specific skill progression level (Dreyfus' model of skill development, x-axis). Dreyfus' skill stages fit well with Blooms' cognitive functionality. At the awareness stage, remembering and understanding of concepts are critical to a learner. With additional training, other skills can be attained by the learner in relation to application and analytical to reach the proficiency stage. With even more advanced opportunities and exposure, the learner reaches the mastery level with the capability of both creating and evaluating skills.

The competency cube is similar to data model, where the cube can be sliced and diced across the dimensions to summarize the data. This cube can now be integrated into a process for detailed data analysis.

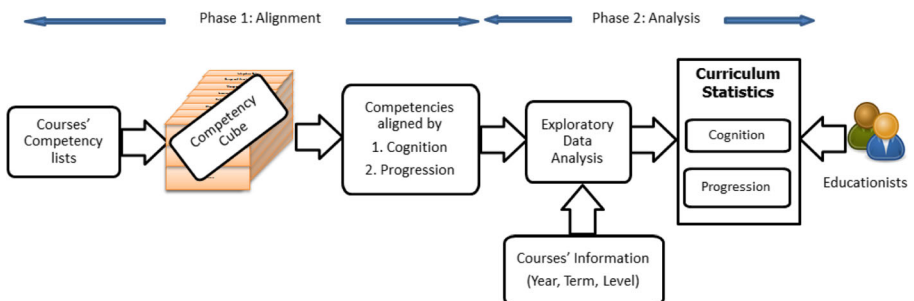


**Fig. 5** Competency cube – an integrated model of learning outcomes, modified Bloom’s taxonomy and Dreyfus’ skill development model

#### 4.2 Automated curriculum design analysis solution architecture

We now describe the process for curriculum design analysis using the competency cube. Figure 6 depicts the automated curriculum design analysis solution architecture created for curriculum design analysis. The architecture consists of two phases; alignment and analysis.

**Alignment** Given the full list of competencies expressed by the instructors, in this phase, the competency cube generates a mapping of the competencies to the cognitive levels, defined in the Bloom’s Taxonomy. To achieve this, Bloom’s action verbs (Krathwohl 2002) are used. A simple text search and POS tagger is executed on each competency to discover verbs for every cognitive level and the competency is aligned



**Fig. 6** Automated curriculum design analysis solution architecture

to the corresponding cognitive level. In this process, if multiple verbs are found, the competency is aligned to multiple competencies. For example, “*Create and evaluate the business process model for a given real world scenario*”, consists of two cognitive functions; *Creating* and *Evaluating*. Therefore, we align the competency to both these levels namely “*Creating*” and “*Evaluating*”. The competencies will also be categorized and aligned by skills stages - progressively. In the above example, the competency will be aligned to the progression level, “*Mastery*”.

**Analysis** In the phase, exploratory data analysis (EDA) (Cook and Swayne 2007) is executed on the course information (year, term, level, etc.) and on the processed competencies to generate the statistics on the overall curriculum. EDA is useful in summarizing the data using various graphical techniques such as box plots, line graphs, bar graphs, etc. These visuals aid the educationists to analyse the curriculum and make decisions. In summary, cognitive statistics aids in analysing the curriculum by thinking levels, while skill progression statistics aids in analysing the curriculum by skill development levels. Some examples of these charts are presented in Section 7.

### 4.3 Competency analytics tool (CAT)

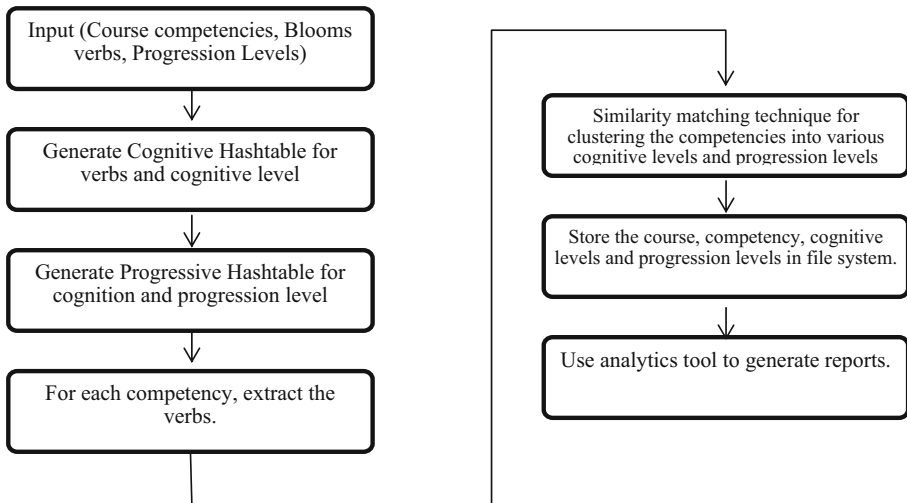
The technical aspects of the tool are shown in the Fig. 7. The tool takes the competencies from the curriculum as inputs and generates reports for analysis. Firstly, two hashtables are generated. Hashtable for cognition is a  $2 \times 2$  matrix that holds verbs and blooms levels. Hashtable for progression is a  $2 \times 2$  matrix that holds blooms levels and cognitive levels. Secondly, from the input competencies, using Parts Of Speech (POS) techniques, the verbs are extracted. The similarity matching techniques are applied to group the verbs to various cognitive levels and progression levels. Thirdly, A table representing the competencies, verbs, cognitive and progression levels is generated. Finally, reports are generated using analytics tools.

The desktop tool is developed using Java programming language and MySQL database. The results from the tool are stored in the database which then connects to SAP Lumira visual analytics tool to generate various reports for the course designers and curriculum designers.

## 5 Recommendations for new courses

When a new course is added to the curriculum, often the course designer starts with defining the high level objectives followed by the course competencies. In this recommendation task, we aim to recommend the blooms cognitive level competencies to the course designer.

Given the course objectives, the goal of the competency tool is to generate the recommended list of competency verbs for a new course. To achieve this, we use the text analytics approach. Firstly, the existing courses which describe the similar objectives at cognitive and learning aspects levels are extracted using text similarity



**Fig. 7** Competency analysis tool (CAT)

technique (cosine). We then generate the unique competency verb list from  $N$  courses where  $V_n$  represents the count of verbs for all the courses in curriculum. For given new course, first the objectives of the course are aligned with the existing the list of courses using text similarity techniques. Finally, a list of recommended verbs is generated for new course where the threshold is set to  $t$ . The details of the results will be described in the experiment section. Table 1 shows the list of similar courses generated for the given course, object oriented application development.

## 6 Dataset

For our experiments we used the core curriculum courses from the BSc (Information Systems) program, at the School of Information Systems, Singapore Management University. The data statistics are shown in Table 2. The course coordinators for each course are required to provide the list of competencies (raw competencies) and map them to program-level learning outcomes. We observed that in many cases, multiple competencies are expressed in a single statement. We also observed that a course might

**Table 1** Recommendation feature: example course and similar courses from curriculum

Objectives for object oriented application development	List of similar courses (Results from the tool)
1. Practice problem solving skills using Java programming language	1. IS software foundations
2. Apply basic concepts of object orientation to a given scenario/context	2. Computational thinking
3. Apply good programming practices and design concepts to develop software	3. Architectural analysis
	4. IS application project

not focus on all the program-level learning outcomes, but only a few. We collected the competency lists, year, term and level (foundation or advanced) information for 14 courses in the core curriculum. Initially, there were 398 raw competences and after applying the alignment process (Phase 1) discussed in Section 4, the total number of aligned competencies increased to 578.

## 7 Experiments

In this section, we first describe our experimental setup followed by the results and discussions.

### 7.1 Setup

Recollect that the course information consists of year, term and level (e.g. foundation or advanced). Some courses are offered in both year 2 (Y2) and year 3 (Y3). Y2 courses are sometimes offered in Y3 for the students' convenience and hence in our experiments we treat them as Y2. Some courses are offered in both the terms and for termly experiments we ignored such courses. Finally, some courses are not under any level and we ignored them for our level analysis. We will first present the cognitive analysis results followed by the progression analysis results.

### 7.2 Cognitive analysis results

Recall that applying EDA on competencies which are cognitively aligned yields the curriculum analysis by thinking levels. Figure 8 shows the curriculum cognitive analysis by year.

We observe that year 1 (Y1) courses majorly focus on “remembering” and “applying”. This is because, Y1 courses such as software foundations and data management are technical in nature and are designed to emphasize learning by application component. Year 2 (Y2) courses majorly focus on “understanding” and “applying”. At the same time, they introduce mastery by creating or developing new products. “Software engineering” course is one of the examples where the students are required to implement a software product. Recall from Section 4 that mastery is aligned to “creating” and “evaluating”. Year 3 (Y3) courses also focus on mastery by leveraging the ability to create solutions. The courses “Architectural Analysis” and “IS capstone project” are taken by students in Year 3 which contribute majorly to mastery and creating products. However, it was puzzling to note that a lot of emphasis was also placed on the users’ “remembering” capability (see Fig. 8). This is something that Year 3 courses should focus less on. This can be an aspect where the educationist might need to intervene to make decisions on the curriculum design for its improvements.

**Table 2** Dataset statistics

Courses	14 (Year1 = 4, Year2 = 6, Year3 = 4)
Raw competencies	398
Aligned competencies	578

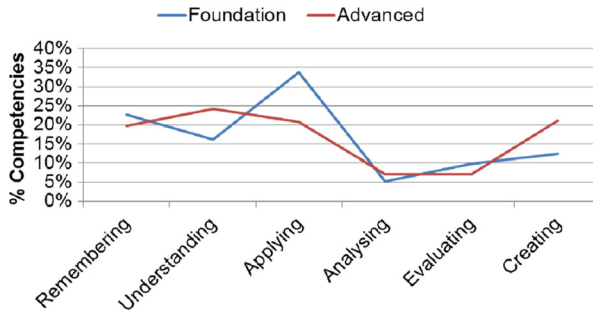


Fig. 8 Cognitive: curriculum design analysis by year

We now evaluate the impact of competencies on curriculum by term. SIS offers core courses only in two terms, Term 1 and Term 2. Figure 9 shows the curriculum cognitive analysis by term. We observe that Term 1 (T1) courses focus on awareness by remembering and in contrast, Term 2 (T2) courses focus on mastery by creating. Both the terms emphasize “applying” as the curriculum is mainly based on business application of technology.

Next, we evaluate the impact of competencies on curriculum by course level (foundation vs. advanced). Figure 10 shows the curriculum cognitive analysis by course level. Foundation courses focus on “remembering” and “applying”. In contrast, advanced courses focus on mastery by “creating”. We also observe that advanced courses also emphasize on understanding and applying.

Finally, we evaluate the impact of competencies on overall curriculum design at various cognitive levels. Figure 11 shows the average cognitive analysis on all the courses. We observe that, in general the curriculum gives importance to remembering, understanding, applying and creating thinking levels. Evaluating and analyzing components are at a very low importance, less than 10%. This can be an aspect where curriculum managers might need to intervene to make decisions on the curriculum design for its improvements.

### 7.3 Progression analysis results

Recall that applying EDA on the competencies that are aligned by skill stages, yields the curriculum design analysis by progression levels. Figure 12 shows the overall curriculum progression analysis. We observed that, proficiency appears to be centered

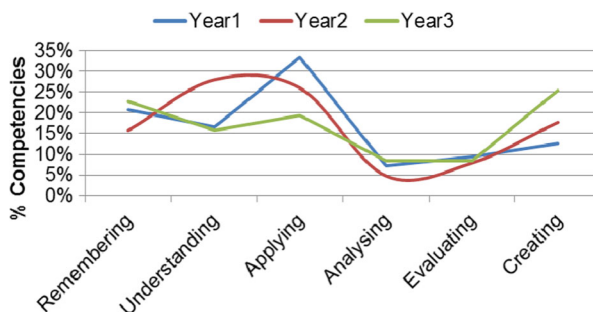


Fig. 9 Cognitive: curriculum design analysis by term

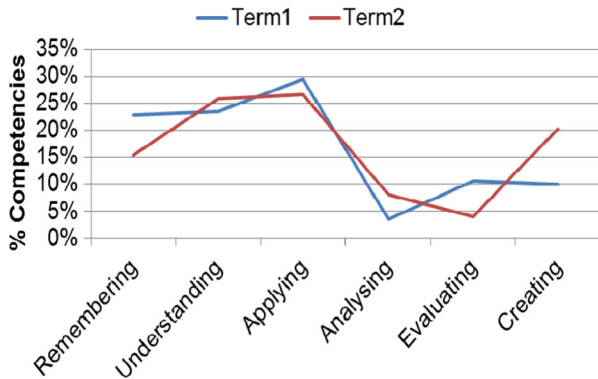


Fig. 10 Cognitive: curriculum design analysis by level

across the curriculum. “Mastery” appears to be similar to “proficiency”, however the number of competencies addressing mastery is lower. As shown in Fig. 12, the mean is lower for mastery compared to proficiency. Awareness has wide variation; this is because some courses gave major emphasis to awareness while others didn’t.

Figure 13 shows progression analysis for each year. We observe that, for all years, awareness is given similar importance. However, the focus on proficiency skills decreased from Y1 to Y3. In contrast, focus on mastery skills increased from Y1 to Y3.

Figures 12 and 13 shows an inconsistent output for awareness. Figure 13 shows that the awareness component is similar for all the years. In contrast, Fig. 12 shows that the awareness component has the highest variation. To understand this behavior, we further analyzed the skill progression functionality at the course level. From the detailed course-awareness results, which are discussed in the next sub-sections, we observed that the focus of awareness has a large variation among the courses across the years which explain the results in Figs. 12 and 13.

#### 7.4 In-depth course analysis - progressions

Yearly or termly curriculum analysis aids in overall analysis at higher level. For example, in previous results we observe that awareness has higher variation at the curriculum level.

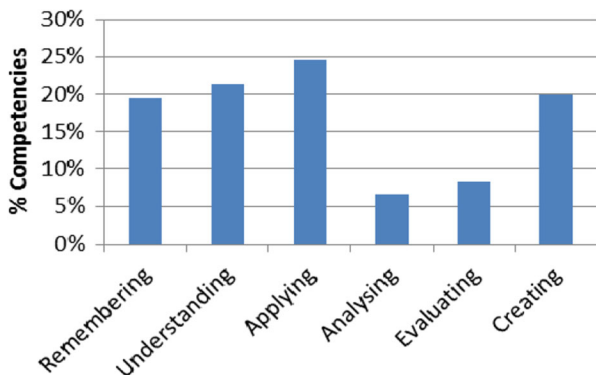


Fig. 11 Cognitive: overall curriculum design analysis



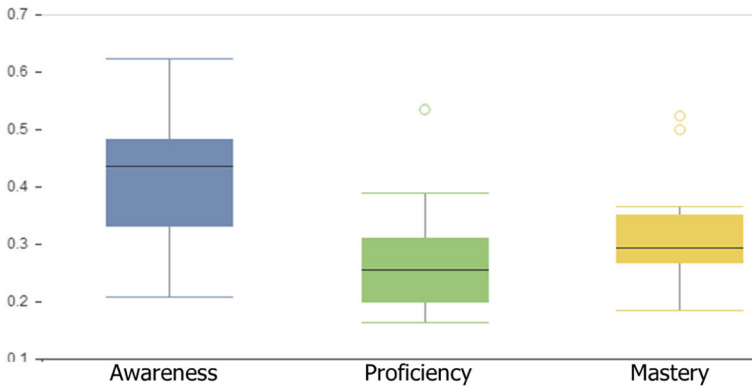


Fig. 12 Progression: overall curriculum design analysis

In order to find the discrepancies within such analysis, an in-depth analysis at course level is required. Figure 13 shows that overall awareness is almost stable across all years. However, from the detailed course-awareness results, in Fig. 14, we observe that the focus of awareness has a large variation among the courses. This explains the discrepancies in Figs. 12 and 13.

To study the details of the courses, we use gap analysis charts such as bubble charts as shown in Fig. 15. Figure 15 shows the in-depth curriculum analysis at the course level for progression functionality. The colors of the bubbles represent courses and sizes represent the number of competencies.

Figure 15a shows the bubble charts (mastery, awareness, course) and (mastery, proficiency, course). The outlier course (a) with very high mastery skills but low awareness and proficiency is “*Architectural Analysis*”. This is a third year course with heavy emphasis on the implementation and deployment skills. The outlier courses (b) with high proficiency skills are “*Software foundations*” and “*Object Oriented Application Development*”. These are first year courses with emphasis on design and create. The outlier course (c) with high awareness skills is “*Process Modeling and Solution Blueprinting*”. This is a second year course with emphasis on analysis and solution design.

We noticed that these experiments aid the curriculum designer to study the competencies of Year 1 courses to provide input for improvements in defining the competencies.

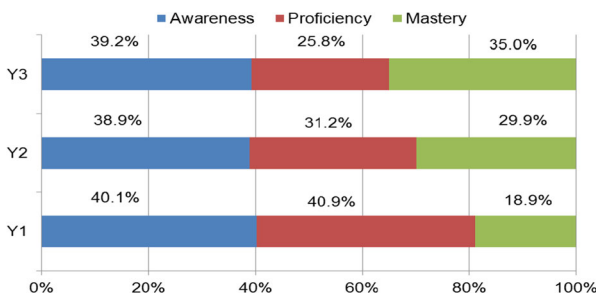


Fig. 13 Progression: curriculum design analysis by year

### 7.5 Recommendation results

To evaluate the performance of the tool, we used 14 courses for our test where for each run, one course,  $C_i$  is treated as a new course, and its competency verb list is treated as the gold truth to compare the results from tool against the actual competencies.  $V_i$  represents the competency verb count of  $C_i$ .  $V_n$  represents the count of verbs for all the courses in curriculum. Recommendation score for the tool generated by the tool for a new course is given by;

$$\text{Recommendation Score for } C_i = (V_n \cap V_i) / V_i$$

Figure 16 shows the recommendation scores accuracy for courses from various years. Overall accuracy is 74.69%. We notice that it is easier to recommend competencies for year 3 (Y3) courses compare to year 1 courses. In our analysis, we notice that year1 competencies are majorly programming courses and the competencies defined are as few, average is 11, unlike the year 2 and year 3 courses where the count of competencies has an average of 23.

### 7.6 Threats to validity

Curriculum analysis consists of three high level dimensions; design (e.g. course design), impact (e.g. job placements) and policy (e.g. vision). In our paper, we only focused on the design analysis. In particular we exploited the competencies for the analysis as they are the building blocks for the course and curriculum design. The results from our experiments on the undergraduate curriculum show the strengths of the curriculum such as balanced cognition levels across the curriculum over the years. At the same time, the experiments identified some of the blind spots in the curriculum such as missing thinking levels for certain courses and low emphasis on evaluation and

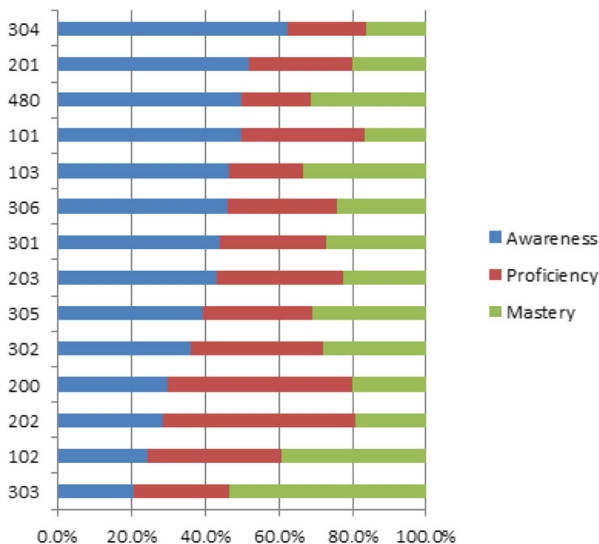


Fig. 14 Skill stages by course - ordered by the “awareness” progression level

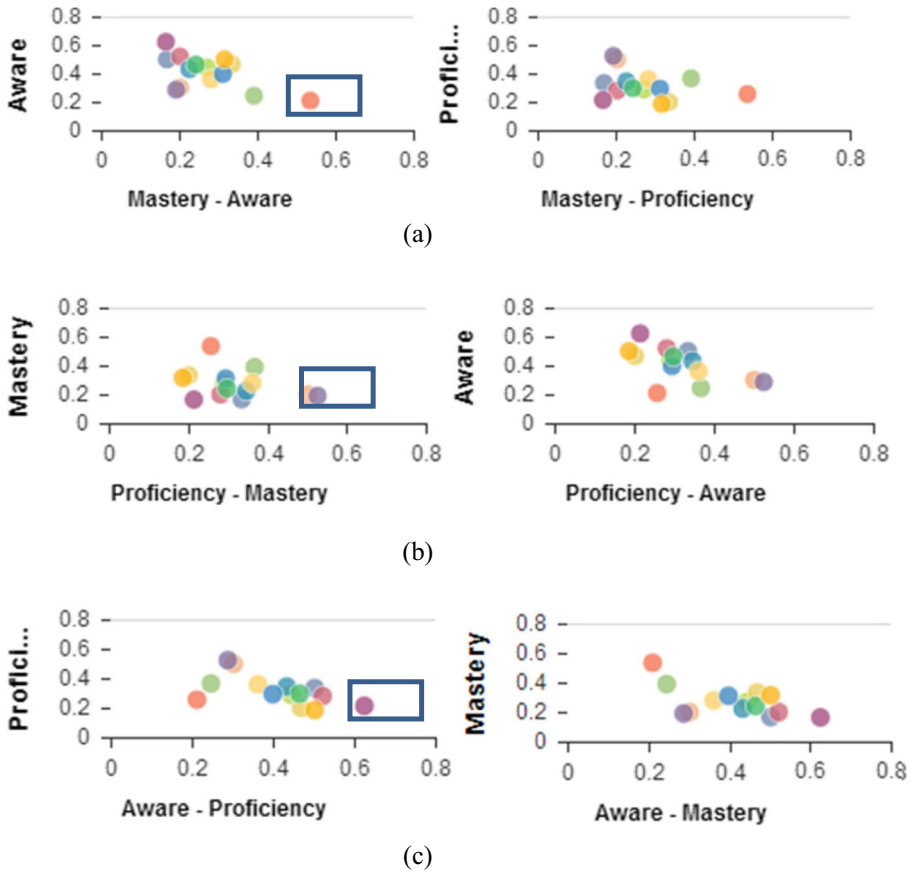


Fig. 15 Progression: curriculum design analysis at course level

analyzing across the curriculum. However, the curriculum analysis at the design dimension is incomplete without studying the impact by other course components such as assessments, resources etc., and we leave such analysis for the future studies.



Fig. 16 Recommendation scores of tool in generating competency verb list for new courses

## 8 Conclusion

Analyzing curriculum is important to not only understand if the current goals are met but also to identify potential problems as early as possible and recommend possible solutions. In this paper, we attempt to analyse an undergraduate core curriculum based on the course competencies. The solution architecture and the tool implemented provides a valuable support to help educationists and curriculum managers to study and if needed to intervene and make decisions on the curriculum design improvements. The tool has also been further extended to provide recommendation, where the competencies can be recommended for a new course. In future it is also interesting to study the application of this solution architecture and the tool to other curricula. Curriculum analysis is incomplete without analyzing other important components of the curriculum such as, course content, course delivery, assessments, resources etc. We leave this for future work.

## References

- Baker, R. S. J.d., & Yacef, K. (2009). The state of educational data mining in 2009: *A Review and Future Visions. Journal of Educational Data Mining*, 1(1), 3–17.
- Baumgartner, I., & Shankararaman, V. (2013). Actively linking learning outcomes and competencies to course design and delivery: experiences from an undergraduate information systems program in Singapore. In *IEEE global engineering education conference (EDUCON 2013)*. Germany: Berlin.
- Bloom, B. S., Engelhart, M. D., Furst, E. J., Hilland, W. H., & Krathwohl, D. R. (1956). Taxonomy of educational objectives: handbook I: cognitive domain. *New York: David McKay*, 19, 56.
- Brabrand, C., & Dahl, B. (2009). *Analyzing CS competencies using the SOLO taxonomy*. New York: In the Proceedings of the 14th annual ACM SIGCSE conference on Innovation and technology in computer science education.
- Burr, L., & Spennemann, D. H. (2004). Pattern of user behavior in university online forums. In *International Journal of Instructional Technology and Distance Learning*, 1(10), 11–28.
- Cook, D., & Swayne, D. F. (2007). *Interactive and dynamic graphics for data analysis: with R and GGobi*. Springer.
- Dreyfus, H. L., & Dreyfus, S. E. (1986). *Mind over machine: the power of human intuition and experience in the era of the computer*. Oxford: Basil Blackwell.
- Ducrot, J., Miller, S., & Goodman, P. S. (2008). Learning outcomes for a business information systems undergraduate program. *Communications of the Association for Information Systems*, 23, 6.
- EU. (2014). The European qualifications framework. European Union Education and Culture DG.
- Feiman-Nemser, S. (1990). Teacher preparation: structural and conceptual alternatives. In W. R. Houston (Ed.), *Handbook of Research on Teacher Education* (pp. 212–229). New York: McMillan.
- Gnana Singh, A. A., & Leavline, E. J. (2013). Competency-based calisthenics of learning outcomes for engineering education. *International Journal of Education and Learning*, 2(1), 25–34.
- Gottipati, S., & Shankararaman, V. (2014a). Learning analytics applied to curriculum analysis. AIS SIGED 2014 Proceedings. 2. <http://aisel.aisnet.org/siged2014/2>
- Gottipati, S., & Shankararaman, V. (2014b). Analyzing course competencies: What can competencies reveal about the curriculum?. *Proceedings of the 22nd International conference on computers in education ICCE 2014: November 30–December 4, 2014, Nara, Japan*. 319–324. Research collection school of information systems.
- Hartel, R. W., & Foegeding, E. A. (2004). Learning: objectives, competencies, or outcomes. *Journal of Food Science Education*, 3, 69–70.
- Jin, H., Wu, T., Liu, Z., & Yan, J. (2009). *Application of visual data Mining in Higher-Education Evaluation System* (pp. 101–104). Washington, DC: In International Workshop on Education Technology and Computer Science.

- Judith, G. C., Ramiah, K., Weist, E. M. G., & Shortell, S. M. (2008). Development of a Core competency model for the master of public health degree. *American Journal of Public Health, 98*(9), 1598–1607.
- Kennedy, D. (2007). *Writing and using learning outcomes: a practical guide*. Cork: Quality Promotion Unit, University College Cork. Internet address <http://www.nairtl.ie/>.
- Kennedy, D., Hyland A., Ryan N. (2009). Learning outcomes and competences: introducing bologna objectives and tools, B 2.3–3, 1–18.
- Khairuddin, N.N., Khairuddin, H. (2008). Application of Bloom's taxonomy in software engineering assessments. In Proceedings of the 8th conference on applied computer science (ACS'08), Subhas C. Misra, Roberto Revetria, Les M. Sztandera, Mihaiela Iliescu, Azami Zaharim, and Hamed Parsiani (Eds.). World scientific and engineering academy and society (WSEAS), Stevens point, Wisconsin, USA, pp 66–69.
- Krathwohl, D. R. (2002). A revision of Bloom's Taxonomy: an overview. Benjamin S. Bloom, University of Chicago. *Theory Into Practice, 42*(4), 216.
- Lister, R., & Leaney, J. (2003). Introductory programming, criterion-referencing, and bloom. In *Proceedings of the 34th SIGCSE technical symposium on computer science education* (pp. 143–147). New York: ACM.
- Mazza, R., & Milani, C. (2004). GISMO: a graphical interactive student monitoring tool for course management systems. In *In international conference on technology enhanced learning, Milan* (pp. 1–8).
- Mostow, J., Beck, J., Cen, H., Cuneo, A., Gouvea, E., Heiner, C. (2005). An educational data mining tool to browse tutor-student interactions: Time will tell! In Proceedings of the Workshop on Educational Data Mining, 15–22.
- O'Neill, G., & Murphy, F. (2010). Guide to taxonomies of learning. In *UCD teaching and learning/resources*. Available <http://www.ucd.ie/t4cms/ucdtla0034.pdf>
- Passow, H. (2012). Which ABET competencies do engineering graduates find most important in their work? *Journal of Engineering Education, 101*(1), 95–118.
- Proli, D., & Dondi, C. (2011). Analysis of learning outcomes approach implementation in European higher education. Project number: 167178-LLP-1-2009-ES-KA1-KA1EQF, European Union Education and Culture DG.
- Raykova, M., Kostadinova, H., & Totkov, G. (2011). Adaptive test system based on revised Bloom's taxonomy. In *Proceedings of the 12th International Conference on Computer Systems and Technologies*. ACM, New York: pp. 504–509.
- Rodolfa, E. R., Bent, R. J., Eisman, E., Nelson, P. D., Rehm, L., & Ritchie, P. (2005). A cube model for competency development: implications for psychology educators and regulators. *Professional Psychology: Research and Practice, 36*, 347–354.
- Romero, C., Gutierrez, S., Freire, M., & Ventura, S. (2008). *Mining and visualizing visited trails in web-based educational systems* (pp. 182–185). Montreal, Canada: In international conference on educational data mining.
- Scott, T. (2003). Bloom's taxonomy applied to testing in computer science classes. *Journal Computer Small Colloid, 19*(1), 267–274.
- Shankararaman, V., & Ducrot, J. (2016). Leveraging competency framework to improve teaching and learning: a methodological approach. *Journal of Education and Information Technologies, 21*, 1299.
- Shen, R., Yang, F., & Han, P. (2002). *Data analysis center based on e-learning platform*. In *Workshop the internet challenge* (pp. 19–28). Berlin, Germany: Technology and applications.
- Vignan, S., Senthilkumar, G., Marthi, N., & Goteti, P. (2011). Integrating learning outcomes and Bloom's taxonomy in web application development course: Experiences from corporate training. In the *Proceedings of IEEE Students' Technology Symposium (TechSym)*, January, Kharagpur, India, pp 11–16.
- Wheeler, D. (2007). *Using a summative assessment alignment model and the revised Bloom's taxonomy to improve curriculum development, instruction and evaluation*. Doctoral dissertation: Syracuse University.
- Whetten, D.A. (2007). Principles of effective course design: What I wish I had known about Learning-Centered Teaching 30 Years Ago. *Journal of Management Education 31*(3), 339–345, pp. 347–357.
- Yoo, J., Yoo, S., Lance, C., Hankins, J. (2006). Student progress monitoring tool using treeview. In proceedings of the 37th Technical Symposium on Computer Science Education, SIGCSE'06. ACM Press. March 1–5, Houston: 373–377.