# TRAINING FOR AUTHENTIC DATA ANALYTICS SKILLS BY ENVISAGING INDUSTRY NEEDS

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**ABSTRACT**

The dynamic environment in the Fourth Industrial Revolution led to the proliferation of information that data now has unattainable scale, speed of access and diversity. The emergence of Data Science driven by the need to deal with data systematically and intelligently puts modern statistical practice as an important weapon. In line with the development of Data Science, the rebranding of statistics education took place in institutions of higher learning that used new labels such as data analytics courses to replace the old name of statistics courses. The objective of this paper is to highlight the implementation of teaching and learning of data analytics on three issues namely the development of the field of data analytics in the country, the challenges of implementing data analytics teaching and learning at the tertiary level and the direction of data analytics teaching and learning. Based on the shift in the paradigm of data analytics pedagogy to practical and interactive integration of conceptual understandings, recommendations for the teaching and learning of data analytics are discussed

## 1. INTRODUCTION

Studies related to the teaching and learning (TnL) of data analytics have gained the focus of researchers and practitioners in the TnL of data analytics. Various discussions were held covering the issue of data analytics TnL paradigm shift, TnL-related problems and difficulties, TnL's focus on the development of statistical mastery as well as TnL innovations and best practices. This issue is parsed in the next section.

Most institutions of higher learning provide opportunities for all students regardless of discipline to take data analytics courses. Data analytics courses are offered with the objective for students to interpret, critically evaluate, and present statistical information , as well as build problem -solving capabilities by using procedures and data analytics correctly (Batova & Ruediger 2019).

The offering of data analytics courses is no exception for institutions of higher learning (HEI) in Malaysia. This is due to the increasing importance of data analytics skills and the need to prepare graduates to face the challenges posed by the rapid development of data -related communication technology. Similarly, research on data analytics learning is gaining increasing attention from local researchers (Krishnan & Idris 2014). Many studies have focused on the interest to see how students 'factors such as subject exposure at previous levels, the educational background they follow influence the extent to which they are able to follow the course well (Auliya 2018).

Several challenges are encountered in the delivery of data analytics curriculum to ensure that learning content meets current needs (Gould et al. 2018). These challenges open up space for learning innovations not only to increase student engagement and interest, but also to produce practical, thorough and responsible statistical users (Hairulliza, Iksan, et al. 2018; Silvestre & Meireles 2017). A paradigm shift in data analytics pedagogy also took place that shifted from a technical approach based entirely on statistical concepts to practical and interactive integration so that analytical skills coincide with multiple fields (Zieffler et al. 2018).

Meaningful learning approaches are applied in data analytics courses compared to other approaches because their effectiveness helps students build a deeper statistical understanding and be able to transfer what they learn in the next class or in the real world (Garfield & Ben-zvi 2009; Hairulliza, Roslinda, et al. 2018). Meaningful learning content is enriched with techniques that can apply active, authentic, constructive, cooperative and goal -based elements (Fan et al. 2015).

The objective of this paper is to highlight the implementation of teaching and learning of data analytics on three issues namely the development of the field of data analytics in the country, the challenges of implementing data analytics teaching and learning at the tertiary level and the direction of data analytics teaching and learning. Based on the shift in the paradigm of data analytics pedagogy to practical and interactive integration of conceptual understandings, recommendations for the teaching and learning of data analytics are discussed.

## 2. DATA ANALYTICS LEARNING IN HIGHER EDUCATION INSTITUTIONS

The dynamic environment in the Fourth Industrial Revolution led to so widespread information generation that the data available today has unattainable scale, speed of access and diversity (Li et al. 2018). The emergence of Data Science driven by the need to deal with data systematically and intelligently puts modern statistical practice as an important weapon. Skills in the form of statistical mastery supported by computer skills are able to derive hidden meanings from data (Abed & Dalbir 2020; Loy et al. 2019). In line with the development of Data Science, the rebranding of statistics education took place in institutions of higher learning that used new labels such as data analytics courses to replace the old name of statistics courses.



In Malaysia, the renewal and rebranding of this course has been welcomed by industry and the public administration. The importance of managing data systematically and intelligently is implicit in the National Industry Policy 4.0 and the Public Data Framework under the strategy of enhancing data integrity and quality. Among the objectives of the framework is to improve the delivery of data analytics -driven services by developing human resource competencies in the field of data science (Sahid et al. 2021). Thus, the emphasis on the development of data -based skills including data analytics and agile decision making based on market changes has become more important than in the previous period.

Local conglomerate companies compete in the job market for new talent to meet the needs of related positions such as Data Analyst, Data Engineer and Data Scientist. The position reflects the scope of work for b working with data but requires different skills from statisticians due to the importance of adopting devices, systems, applications and equipment to deal with large and complex sized data (Li et al. 2018). Agencies under the civil service also intensified training and courses to improve the skills for their staff (Sahid et al. 2021).

In line with the increasing importance of data analytics TnL in Malaysia, there is a need to develop more coherent data analytics TnL content at the tertiary level (Krishnan & Idris 2014). In detail, there are three questions posed: What is the content of TnL appropriate to the Malaysian context; How students 'understanding can be developed; and How student understanding can be measured. To answer and analyse these three important questions that occur at the local level, the strategy implemented is to look at past studies at the inter -racial level that directly raise the same concerns. The questions posed are answered in the discussion shortly.



Based on the background of TnL data analytics which is technical in nature, many instructors emphasize the technical aspects in the delivery of this course. This includes the presentation of material laden with Mathematical content and formulas as well as burdened with difficult theories (Forbes 2012). Student acceptance of such an approach is low, hence a paradigm shift is triggered in data analytics pedagogy (Hassad 2014). More practical and interactive methods are proposed by involving experiential planning and problem solving that require careful thinking and reasoning (Garfield 2002). Instructors 'response to these changes turned out to be positive, for example students were excited about the application of data analytics concepts in everyday problem solving involving exploratory elements (Nguyen 2016).

A critical problem plaguing data analytics education is that a topic is often taught as an isolated topic, rather than explicitly combined with other statistical concepts or linked to other domains (Tobías-lara & Gómez-blancarte 2019). In addition, students are assumed to be able to assimilate key statistical concepts required and reach accurate conclusions (Leppink et al. 2013). As a result, the level of understanding that allows students to make connections to these concepts is not achieved as expected. This is also demonstrated through unsatisfactory data analytical problem solving and there are conceptual understanding gaps that need to be addressed (Tobías-lara & Gómez-blancarte 2019). In addition to the conceptual understanding gap, some of the important challenges faced by data analytics educators are elaborated in the next section followed by a peeling of conceptual understanding in more detail.



## 3. DEALING WITH CHALLENGES AND ISSUES

Although the TnL paradigm of data analytics focuses on the development of conceptual understanding, learning toward conceptual understanding does not necessarily occur in all data analytics course offerings. This stems from several factors including the difficulty of instructors preparing the conceptual understanding component as opposed to procedural patterned knowledge which consumes time, knowledge and energy (Crooks et al. 2019). It also has to do with the next factor.

Data analytics course offerings are offered at most institutions of higher learning across disciplines (Forbes 2012). As a result, more and more instructors are needed to conduct data analytics courses. The question is, to what extent do educators have content knowledge regarding data analyticsm(Turegun 2014). Instructor attitudes were found to play an important role in enhancing data analytical knowledge through several strategies (Posner & Dabos 2018). This includes collaborating with mentors who are more senior teaching partners, attending ongoing TnL workshops and following the development of relevant TnL research.

With regard to the development of conceptual understanding, students generally construct concepts within the framework of existing knowledge of learning outcomes formally or through their experiences. Students adapt their knowledge structure to use with the results sometimes inaccurate but sometimes it works correctly in other contexts(Crooks et al. 2019). Thus, the challenge of educators in this regard is to identify difficult concepts and then formulate intervention strategies to improve TnL (Broers 2009).

Instructors of data analytics -related courses are commonly faced with a reluctant attitude among students and should find ways to help students become practical, thorough and responsible users of data analytics (Tishkovskaya & Lancaster 2012). Students in data analytics courses will appreciate learning more if the course involves activity-based assignments and group work (Chance et al. 2007). The task aims to help students improve their understanding of the concept of data analytics. Each assignment requires feedback from the instructor to provide students with important information about actions and opportunities for students to develop themselves and understand solution mechanisms (Smith & Capuzzi 2019).

The TnL approach to data analytics courses in higher education requires a lot of attention to tools that allow students to be attracted to the material and engage in learning (R. Jones

2019). In this regard, much effort is focused by the teaching staff to improve the teaching and learning of data analytics to increase students ’interest and understanding. Through the commitment shown by instructors, negative perceptions of students who tend to say data analytics courses as boring can be changed and it is impossible to have fun learning them (Chance et al. 2007).

Further challenges involve the assessment and measurement of students taking data analytics courses. Assessment instruments needed should help teachers with methods equitable and practicable to measure the cognitive abilities of students, including reasoning statistics and other skills that can be customized according to discipline students follow (Tobías-lara & Gómez-blancarte 2019). Data analytics course evaluation is appropriately linked to course learning outcomes in order to reflect the alignment between course planning and implementation(Sabbag & Zieffler 2015). Assessment is also recommended to include formative and summative forms for the improvement of the learning process (Franklin & Garfield 2006). Better yet, assessment has the following three elements: assessment for learning outcomes, assessment as learning and assessment in learning (Earl & Katz 2006).



It is hoped that the issue of assessment of student comprehension will be able to answer the third question, which is how student comprehension can be measured. In summary, the measurement of students' understanding should be made through formative and summative assessments that encourage students to explore and appreciate learning.

## 4. WAY FORWARD

Analytical TnL content of data generally has two important components (Bisson et al. 2016). First, procedural knowledge that is related to the use of systematic data analytical measures for problem solving. Second, conceptual understanding is related to the knowledge of basic concepts, key principles and the relationship between concepts. Conceptual understanding also refers to a network or structure that connects separate concepts representing a single domain including also an understanding of the key principles underlying the domain and directly related to the real world (Dolores-Flores et al. 2019).

Conceptual understanding is important in the learning of any domain because it involves cognitive processes that allow individuals to discover real relationships between several ideas (Leppink et al. 2013). The discussion of conceptual understanding provokes much debate, yet general acceptance agrees that conceptual knowledge begins with the connection between diverse knowledge and develops in parallel with skill improvement (Broers 2009). Among the debates that arise is how to define a concept while the conceptual understanding itself is relative according to use in their respective fields. In addressing this issue, a concept can be defined as it is seen, understood to be used by its experts or practitioners in the relevant industry (Bisson et al. 2016; Vats et al. 2020). As such, the proposed definition is independent of a number of linguistic terms that can restrict the expression and description of concepts to the point of being difficult to appreciate.

Interest in studying the development of students 'conceptual understanding in data analytics TnL has been increasing in recent times (Rittle-Johnson & Schneider 2014). Furthermore, the focus of data analytics learning previously on mathematical concepts supported by data analysis, is now shifting to experiential planning and problem solving that require careful thinking and reasoning (Garfield 2002; Hassad 2014).

Thus, it is not surprising that educational interventions and data analytics education policy changes are heavily focused on enhancing students 'conceptual understanding (Hybsova & Leppink 2015; Tobías-lara & Gómez-blancarte 2019). Conceptual understanding is important in analytical learning to ensure that students do not memorize what is learned (Broers 2009). Conceptual understanding gives students advantages including to think critically and act more flexibly, transfer knowledge to other problems or more challenging situations, implement data analytical procedures in an orderly manner and make decisions fairly ((Crooks et al. 2019).

Through the analysis in this section, the first question posed regarding the appropriate TnL content in the Malaysian context can be answered by suggesting a focus on conceptual understanding. Conceptual understanding is closely related to statistical mastery. Statistical mastery refers to the ability to use and relate statistical concepts as well as issue arguments with statistical ideas and make data -based justifications (González Marqués & Pelta 2017). Statistical mastery is useful for solving data analytics -related problems in the dominated domain (Dierker et al. 2016).

Statistical mastery can be measured by an individual's ability to solve problems involving analysis involving the real world including critical thinking and making judgments based on data and situations (Gould et al. 2018).Statistical mastery is the result of a conceptual understanding of important ideas in statistics. Students with a strong conceptual understanding are able to build problem-solving abilities by using procedures and data analytics correctly (Tobías-lara & Gómez-blancarte 2019). These specific skills related to statistical mastery are often referred to as statistical reasoning (Garfield et al. 2015).

The conceptual understanding of data analytics in the context of data analytics learning is closely related to statistical reasoning (Bude 2007). This is because statistical reasoning includes the skills of making arguments and connections regarding statistical ideas as well as using statistical information (Garfield 2002). Statistical thinking and reasoning have some similarities but there are important differences because reasoning is not just thinking but involves the search for concept -based specific evidence as well as making generalizations to larger cases and situations (Garfield et al. 2015).

Statistical reasoning can be defined as a way of making arguments with the analytical idea of statistical data and making justifications based on statistical information (Garfield & Ben-zvi 2009). This involves interpretation based on data sets, graphical representations, and statistical summaries. Most statistical assumptions combine ideas about data and opportunity, leading to inferring and interpreting statistical results (Zieffler et al. 2018). Reasoning is underpinned by a conceptual understanding of important ideas, such as data distribution, data centralization, data scattering, event correlation, event uncertainty, event randomness, and data sampling(Tobías-lara & Gómez-blancarte 2019).

Statistical reasoning is an interesting and important topic and is even a skill required by many professionals in different domains (Garfield et al. 2015). For the psychological domain, these skills involve the assessment and decision -making of statistical information, while for the medical profession, the related skills are the understanding of risks, opportunities, and health test results (Leppink 2017). For the writing and journalism industry, such skills involve the description and critique of statistical information in the media (Nguyen 2016).

To achieve a robust conceptual understanding of building statistical mastery, there is a need to use learning approaches that enhance the achievement of conceptual understanding and test its effectiveness in the function in question (Tintle et al. 2012). Various interventions were conducted in data analytics TnL research to support this goal. This issue is discussed in the next sub-section.

## 5. CONCLUSIONS

This paper offers details the problems, importance and strategies of enhancing conceptual understanding in the teaching and learning of data analytics at the tertiary level. This also answers three questions related to the direction of teaching and learning of data analytics in local institutions of higher learning. Further, the study refines elements in meaningful learning approaches and how they are implemented in data analytics learning.

Among the major problems identified in data analytics learning are closely related to the problem of having a clear and in -depth understanding of the topics studied. This problem encourages students to tend to memorize what they learn. Causes of this problem include unsound conceptual relevance. Failure to develop an in -depth understanding of concept integration affects students 'learning clarity and retention of knowledge. Data visualization techniques seek to optimally enhance learning interactions that highlight the interrelationships between concepts.

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