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# Developing a Data Analytics Mindset

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*Completed Pedagogical Study - Abstract*

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## Abstract

Companies increasingly view data analytics and associated fields as key to their future competitive strategy, yet the supply of potential employees available to fill these roles is far below needed. While colleges and universities have responded *by* increasing relevant programs of study, the number of students enrolled in these programs is small by comparison to the number of job openings. In this paper we address the underlying question of how to engage university students at all levels in analytics - from the end user who can interpret analytics output, to the data analyst who can utilize sophisticated software to create knowledge from data, to the data scientist who can write computer code and develop software as needed for specialized applications. We are informed by practitioners and learning theories, and we research the underlying traits of an analytics mindset such as intellectual curiosity and relate engagement in analytics to cognitive learning styles. Finally, we use literature on High Impact Practices (HIP) to identify teaching activities in order to engage students in analytics.

### Keywords

Analytics, business intelligence, intellectual curiosity, cognitive styles, pedagogy, high impact practices.

## Introduction

Analytics-related employment has become one of the most sought out set of roles across the globe. A range of skills is needed from smart decision making to sophisticated technical abilities to reflect various job functions such as data users, data analysts, and data scientists (Phillips-Wren et al., 2018). However, the skills and knowledge needed to be successful to conduct the complex data analyses required by organizations are mostly lacking in the existing pool of candidates according to many practitioner sources and surveys (Bloomberg 2018). The McKinsey Global Institute reported that by 2018, the U.S. would need 140,000 to 190,000 people with deep analytics skills (Manyika et al., 2011). To address business needs, the Business Analytics Congress 4 (BAC4), a pre-ICIS workshop sponsored by SIGDSA, organized a panel entitled "AACSB Resources for Building a Business Analytics Program" on December 13, 2016. The panel focused on analytics program and curriculum development initiatives by AACSB to help universities contemplating Business Analytics programs. Panelists shared resources that provided a mix of curriculum content, pedagogy, and access to practitioner software and hardware.

Overall the panel confirmed the continuing growth in the need for analytical skills in industry. The higher education environment is rapidly changing as AACSB Standard 9 emphasizes data analytics and STEM-related skills, especially in the accounting discipline. There is movement to connect and engage academia and industry by developing analytics programs that cut across the spectrum of different majors in the business school to amplify impact. In describing the specific analytics skills needed, panelists identified both soft skills (the ability to communicate clearly and effectively and explain the logic and truth behind the results of data analysis) and technical skills (the ability to manipulate huge amounts of data to provide insights for managers and the organization by understanding the nature of the data, and doing regression and statistical analyses). Panelists also commented on the roles that emphasized each type of skillset.

Underlying the acquisition of both technical and soft skills, the panelists pointed to students' need to cultivate a mindset that would drive them to ask more questions and be generally more inquisitive about the data, business rules, context, etc. surrounding the analytical work in which they engage. The practitioner realm is interested in employees with 'curiosity' as a trait in data analytics candidates. In support of this point of view, Burtch Works Recruiting (2018) presents skills that employers are looking for in 2018 and describes 'Intellectual Curiosity' as continuing to lead the non-technical skills sought in this space. Academic literature also discusses curiosity as essential to enhance learning, especially in the psychology and sociology streams of research. However, there is scant evidence of the examination of curiosity in information systems research.

In this paper, we seek to identify underlying attributes that we seek to develop in the analytics workforce of the future and pedagogical approaches to nurturing characteristics such as intellectual curiosity. Thus, we address the issue from the viewpoint of the educator and ask the research question: *How can university educators and other stakeholders encourage and develop a data analytics mindset in students?*

To address the question, we first present the practitioner perspective and a brief literature review of what underlying traits and learning styles might help in developing an analytical mindset needed for data science/analytics careers. Using research on High Impact Practices (HIP) to inform best practices in teaching, we then identify pedagogical activities related to data analytics.

# Background

## *Intellectual Curiosity and Cognitive Styles*

Practitioner articles on traits of effective data scientists or data analytics teams such as "Six qualities of a great data scientist" (Datascope Analytics, 2014) and "Most Important Trait for a Data Scientist? Curiosity" (Kaye, 2013) present curiosity as a key skill for individuals dealing with data. According to Sullivan (2014) in "Getting the right data scientist to ask the wrong data question" published in the *Harvard Business Review*, "Fundamentally, what sets a great data scientist apart is fierce curiosity – it's the X factor. You can teach the math and the analytical tools, but not the tenacity to experiment and keep working to arrive at the best question – which is virtually never the one you started out with."

Curiosity is the exploration of novel stimuli, led by feelings of interest and uncertainty, in order to acquire new information (Berlyne, 1949). Curiosity has been studied by many researchers as a major driver of educational performance (Komarraju et al., 2011). Curiosity can be differentiated as epistemic and perceptual curiosity (Reio et al., 2006). Epistemic curiosity refers to individual differences in seeking out opportunities for intellectual engagement, acquiring facts and knowledge; whereas, perceptual curiosity is evoked by visual, auditory, and tactile stimulation and refers to a motivation to experience and feel. There are many different factor compositions of intellectual curiosity in the literature. Overall, this desire to invest time and energy into learning more about the unknown or intellectual curiosity is seen as a strong indicator of high academic performance. It has led to the encouragement of curiosity into the curriculum of educational institutions (Maki, 2002). More recently, intellectual curiosity has found a voice among analytics practitioners and analytics organizations as an important skill to cultivate to achieve analytical success. In organizations, challenges often surround identifying and trying to understand the root cause or asking why questions that require conducting data analyses for meaning (Calugar, 2015). Investing in people who have an 'intellectual hunger' to figure things out are seen as developing strong analysts that help make effective decisions that drive return on investment (Bolton, 2017).

While intellectual curiosity describes a person's engagement and interest level in a subject, cognitive style refers to the way that people learn about a subject once they are engaged. "Learning styles are the beliefs, preferences and behaviors that people employ in order to learn in a certain situation" (Nozari and Siamian, 2015, p. 40). The literature on learning styles recognizes that learners use distinctive strategies that can be generalized for information processing, reasoning and developing new concepts (Evans and Over, 2013). Some studies suggest that when education and materials better align with students' cognitive styles, students demonstrate improved academic achievement (Al-Saai and Dwyer, 1993).

Learning styles refer to the ways that learners "gather, sift through, interpret, organize, come to conclusions about, and 'store' information for further use" (Chick, 2018). One well-known way to categorize learning styles, called VARK, is by sensory approach: **v**isual, **a**ural, verbal [**r**eading/writing], and **k**inesthetic (Chick, 2018). For example, does the individual learn best by seeing the information such as with a diagram (visual), through hearing the information spoken (aural), through reading and writing about the information (verbal), or by touching the information such in an activity (kinesthetic).

Although there are over 70 different learning styles schemas (Chick, 2018), the fundamental idea is the same for all learning styles research: each of us has a preferred learning style, and we learn best when information is presented to us in this style. Research suggests that most of us utilize a mixed strategy of learning styles so that our primary style is supported by using the other ways that information is presented and then processed (Chick, 2018).

# Pedagogical Approaches for Analytics

AACSB promotes teaching and learning practices that have been shown to be beneficial for many university students in all fields and are supported by research (AACSB, 2018). These practices have become known as High-Impact Practices (HIP). Currently the identified HIP are: first year seminars and experiences, common intellectual experiences, learning communities, writing-intensive courses, collaborative assignments and projects, undergraduate research, ePortfolios, service learning and community based learning, internships, capstone course and projects.

Kuh (2008) points out that these practices are unusually effective for several reasons: (1) students must devote considerable time and effort to a purposeful task that deepens their investment and commitment; (2) students must interact with faculty and peers about substantive matters over an extended period of time; (3) students often experience diversity through the activities; (4) students receive frequent feedback over time; (5) students see their learning in different settings on and off campus; and (6) students experience deeper relationships and develop broader perspectives that can alter their view of self and others.

Using HIP, it is possible to design pedagogical approaches that are appropriate to analytics and serve to increase intellectual curiosity. Using theories of cognitive styles, we can further suggest activities that capitalize on a learner's underlying cognitive approach with specific teaching activities. In our presentation, we will identify pedagogical activities to enhance student learning and engage students in analytics.

## Summary and Conclusions

This abstract has presented a perspective on creating an analytics mindset that integrates high impact practices with the views of stakeholders, cognitive styles of learners, and traits associated with data science such as intellectual curiosity.

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