# Teaching Data Analysis with Interactive Visual Narratives

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**ABSTRACT**

Data analysis is a major part of business analytics (BA), which refers to the skills, methods, and technologies that enable managers to make swift, quality decisions based on large amounts of data. BA has become a major component of Information Systems (IS) courses all over the world. The challenge for IS educators is to teach data analysis – the foundational BA concepts – to early years undergraduate students who commonly have an aversion to statistics as well as poor problem-solving skills. This article describes the development and evaluation of a learning intervention, Interactive Visual Narratives (IVN), which is informed by previous research into the efficacy of interaction, visualization, and narratives across a variety of learning contexts. The results suggest that a combination of interactive visualizations and narratives can improve the acquisition of data analysis knowledge, facilitate essential skills in problem analysis and the application of BA solutions, and enhance student engagement. These findings provide useful insights for improving students' learning outcomes and engagement.

**Keywords**: Narratives, Interactive data visualization, Business analytics

## 1. INTRODUCTION

Business analytics (BA) is an emerging discipline which defines and promotes the use of "techniques, technologies, systems, practices, methodologies, and applications that analyze critical business data to help an enterprise better understand its business and market and make timely business decisions" (Chen, Chiang, and Storey, 2012, p. 1166). BA tools, resources, as well as skills and experience in data analysis are in demand because proactive business organizations are quick in their attempts to capitalize on the benefits of big data (Manyika et al., 2011; Schroeck et al., 2012). The common understanding of big data focuses on the advantages of the sizeable volume of data available to individuals and organizations for analytics and insight generation. However, a more prevalent business view of big data extends this intuition to include the three Vs of data – its volume, variety, and velocity (Russom, 2011) – which bring into focus the potential difficulties of big data processing. With the promise of big data benefits and the challenges in its handling, it is predicted that in the next few years BA will become one of the management's top priorities (Gartner, 2012), especially in the area of data analysis in support of business decision-making and action planning. This has created an unprecedented demand for Information Systems (IS) graduates with higher degree qualifications and significant BA skills (Stubbs, 2015). Moreover, a recent study by the McKinsey Global Institute predicts that by 2018 the U.S. market alone will face a shortage of between 140,000 and 190,000 analytics professionals, in addition to 1.5 million managers and analysts to work in the big data space (Manyika et al., 2011). In order to cater for future demand of BA graduates, higher education institutions are designing new BA curricula drawing synergies from different disciplines such as Business, Statistics and Mathematics, Information Systems, and Computer Science (Stubbs, 2015).

In spite of the enthusiasm of academic staff to deliver new BA programs, the effective delivery of new university BA courses faces numerous challenges. These challenges include issues such as unavailability of suitable teaching tools and resources, fast-changing technology and curriculum, and a shortage of versatile academic staff who can teach multidisciplinary content (Wixom et al., 2014). To compound these problems, BA curriculum includes complex and abstract subject matter, such as business statistics, that has been traditionally difficult to teach, especially to students with very little mathematical knowledge (Murtonen and Lehtinen, 2003; Mvududu, 2003; Prabhakar, 2008) and little exposure to business (Harmer, 2009).

The project reported in this article addresses some of these challenges by adopting an innovative approach to teaching key foundational BA concepts, including data analysis in particular. We rely on students' experiences with personal technology (such as smartphones, tablets, and laptops), their familiarity with visual interaction with computer software (such as that offered by gaming consoles), their intuitive understanding of business problems, and their general knowledge. Our approach follows current industry practices where interactive visualizations are being successfully deployed in business, science, and information management (Keim et al., 2008). In these deployments, the natural perception and cognitive abilities of humans are being utilized to visually interact with data in search of interesting features and patterns (Brodbeck, Mazza, and Lalanne, 2009). Specifically, this article reports on the design and evaluation of a learning environment which combines interactivity, information visualization, and storytelling – referred to as Interactive Visual Narratives (IVN) – to teach data analysis concepts to first-year undergraduate students in IS and Business studies.

## 2. RATIONALE FOR INTERACTIVE VISUAL NARRATIVES

As we create BA curricula drawing on the reference disciplines, we are also confronted with a number of challenges. For example, to convey the fundamental data analysis concepts, which borrow from Data Mining and Statistics, teachers need to transfer to students cognitively demanding abstract notions, mathematical methods, and complex theories (Wixom et al., 2014). To recreate business contexts for data analysis, which are based on Business and Information Systems studies, teachers struggle with the creation of an authentic business experience – to involve people, products, processes, and transactions – where students could engage in behavior appropriate for the commonly encountered business situations (Harmer, 2009). Thus, in order to facilitate effective learning of BA – that is, data analytics in a business context – it is important to align the course business and technical content, as well as its instructional events, with students' cognitive processes and their patterns of behavior (Kennedy, 2004; Renkl and Atkinson, 2007). Consequently, our IVN Learning Design Model (see Figure 1) was based on the work of Kennedy (2004) who postulates integration of instructional events, and cognitive and behavioral processes, to support effective learning. We then further enhanced the model to support learning of specific BA skills with interactive data visualizations and authentic business narratives (IVN).

The IVN Learning Design Model has three main elements: *a learning activity*, its *triggers*, and its *outcomes*. A learning activity is a design of a learner's intended cognitive and behavioral processes in response to instructional events. Outcomes are the immediate results of learning, including knowledge and experience, as well as the learner's engagement with the activity (externalized attitude). Learning outcomes and engagement translate into motivation (internalized attitude) to continue active participation in the learning activity, which thus also makes

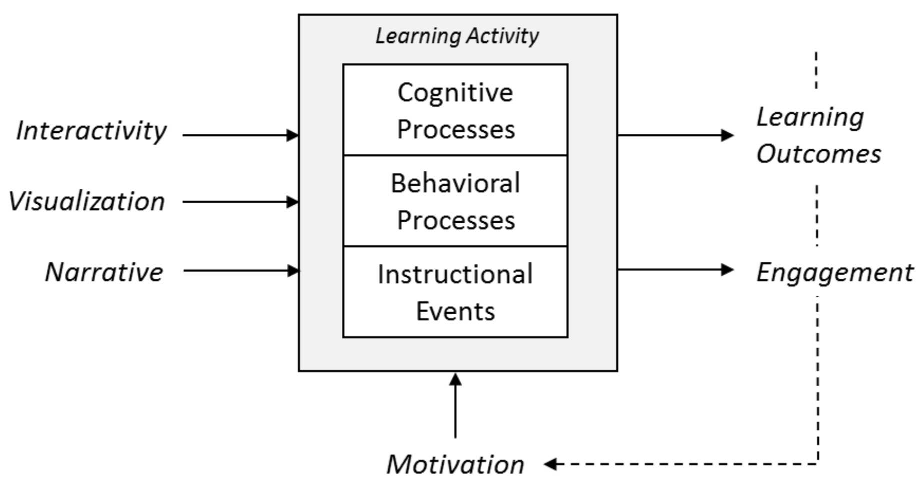


**Figure 1: IVN Learning Design Model (Adapted from Kennedy, 2004)**

motivation a potential trigger. Other triggers include the anticipated learner's interactions with visualized and contextualized data (interactivity, visualization, and narrative). In the following paragraphs, we will further explore the three elements of the IVN model.

*Triggers.* In the IVN model a learning activity in data analysis needs to be infused with interactive data visualizations and guided by the authentic business narratives (IVN triggers), in addition to the learner's motivation fueled by positive learning outcomes and engaging learning activity.

In many academic fields such as science, mathematics, and engineering, data visualization has a track record in imparting knowledge of abstract and complex ideas to students (Brodbeck et al., 2009; Yarden and Yarden, 2010). By using business data visualizations rather than symbolic representations, we can potentially offload a large part of students' cognitive processing to the visual system. Moreover, well-designed visual representations improve comprehension, memory, and decision-making (Heer, Bostock, and Ogievetsky, 2010). Because visual forms portray information in a concrete and spatial manner, they aid students in problem-solving (Brodbeck et al., 2009). We argue that learning activities with graphical representations of (primarily numerical) data are capable of assisting students to understand abstract ideas, as well as form mental representations of complex analytics concepts.

Interactivity with visual forms is a cornerstone of designing effective learning and an essential aspect of any experiential learning environment (Domagk, Schwartz, and Plass, 2010). Well-designed interactivity allows learners to explore and manipulate information, and is capable of immersing students in a deep cognitive process, which results in better learning outcomes and increased student engagement (Kennedy, 2004).

Narratives can help to explain information in its larger settings, provide continuity of ideas captured in data and their visualizations, and direct students' attention to important insights that can be drawn from data (Ware, 2012). In the context of data visualization, narratives can thus be used to contextualize, describe, annotate, and explain data and its visual forms, and intellectually engage the audience. In essence, narratives are an important sense-making tool for data, their visualizations, and in general, the world reflected in data (Bruner, 2002; Polkinghorne, 1988). Some of the best-known story-based techniques, such as case studies, role-playing, games, and simulations are often deployed in higher education (Rossiter, 2002). Empirical research on the use of narratives to support teaching of data analysis and statistics, however, is relatively scarce (Novak, 2014) and has yielded mixed results. For example, while McCarthy (2012) found that in engineering education, simulations with narratives improved student engagement, Novak (2014) on the other hand claimed that narrative-based simulations were ineffective in teaching statistics to graduate students, both in terms of learning outcomes and engagement. Confronted by these counterintuitive findings, the author of the latter study calls for further studies in this area to investigate a number of factors that could potentially explain such phenomena as the cognitive load involved in following a storyline or the impact of participants' age and prior experience on understanding and the ensuing learning outcomes.

*Learning Activity.* At the center of the IVN model is a learning activity, which identifies a series of instructional events, each describing the series of steps needed for students to complete their learning tasks (behavioral processes) and what mental processes the tasks should involve or exercise (cognitive processes). Examples of instructional events in teaching BA could include a simulation of activities leading to the collection of business data. As instructional events are designed with very specific learning objectives in mind (Gagné, 1977), the aim of such a simulation may involve learning the difference between properties of a collected sample and properties of the entire population.

Behavioral processes determine how students act or react when they are presented with a learning activity. In a simulated data collection, these activities may be as simple as clicking on icons of animated customers entering or leaving a shop (see Figure 2), or they could be as complex as planting geolocation markers indicating significant observations or analyzing transaction logs of customers purchasing products online (as used in more advanced analytic subjects (Cybulski, Keller, and Saundage, 2015)).

Kennedy (2004) suggests that the association between instructional events and behavioral processes is bidirectional as instructional events induce a behavioral response from a student, and, similarly, the student response determines what instructional events could take place next.

Another aspect of the learning activity design is to describe students' cognitive activities when engaging with an instructional event. Cognitive processes are mental acts that students perform to acquire, integrate, and organize new information (Domagk et al., 2010; Kennedy, 2004). In the data collection example, the process of repetitive clicking on the icons of animated people entering or leaving a shop creates an association between a real business situation (e.g., a customer's arrival in a shop), its abstract representation of data (e.g., inter-arrival time), and through the collected data set, a sample of business data and its distribution.

*Outcomes.* The final element of the IVN model is the outcomes of a learning activity, some of which can be defined in terms of students' skills and knowledge, but also others which are related to student engagement with the designed activity, which provides a motivational feedback loop for the learning process. To better understand the nature of learning in relation to its objectives, student behavior, and student cognitive processes, we classify learning outcomes into different levels of cognitive attainments.

In order to explain and measure cognitive aspects of learning, for this study, we developed a quiz based on Bloom's original Taxonomy (Bloom et al., 1956). The revised Bloom's model (Krathwohl, 2002) was developed to factor in different types of knowledge in student learning, such as factual, conceptual, procedural, and metacognitive. As the focus of this study was on students' cognitive and behavioral processes, the original Bloom's taxonomy was considered a better fit with the study objectives.

According to Bloom (1971), learning commonly occurs at six cognitive levels:

- **Knowledge:** This foundation level indicates an ability to recall data or information.
- **Comprehension:** This level is used to describe an ability to understand intended meaning and interpret given instructions/problems in one's own words.
- **Application:** This level represents an ability to use a concept in a new situation.
- **Analysis:** This level indicates an ability to break down a concept into its components and also reason about their mutual relationships.
- **Synthesis:** This advanced level involves building a structure/pattern ("a whole") out of many separate parts.
- **Evaluation:** This highest level indicates an ability to make informed judgments about the value of ideas/solutions/proposals.

In our study, we hypothesized that learning activities, which involve instructional events and which are well aligned with the IVN triggers (specifically interactivity, visualization, and narratives), could lead to better learning outcomes, while maintaining high student engagement, especially when compared with similar activities devoid of such learning triggers.

In the following sections, we will describe the context and processes of deploying the IVN Learning Design Model in teaching data analysis, and the methods used in studying the outcomes of the IVN-based approach.

## 3. THE IVN LEARNING DESIGN MODEL

To appreciate the objectives and methods of our research project, it is important to understand the larger context of teaching data analysis at Deakin University (Australia) which hosted this project. At that institution, Business Analytics is a specialist sequence in a Bachelor of Information Systems and a major sequence in a Bachelor of Commerce degree. Each sequence covers a range of problem-solving, information management, data visualization, and analytics topics.

The analytics sequence is surrounded by business subjects and topics which motivate learning of analytic methods and which provide concepts and methods interwoven into analytic cases, projects, and assignments. Data analysis and visualization are the cornerstones of many analytic units, thus, the IVN model and its methods were applied across a range of subjects and topics.

However, the controlled evaluation studies of the IVN approach were first conducted in the selected BA topics, which are commonly perceived by first-year students as their most difficult, abstract, dry, and uninteresting topics, and which include several aspects of data analysis, statistical methods, and decision-making. While the domain of study was focused on the application of statistical methods, students acquired skills across a range of typical analytic processes, which included data collection and analysis, problem-solving, and decision-making, along with providing recommendations to management. The following section illustrates and explains the process taken in designing many different learning activities in our BA subjects.

The learning activity at the center of the IVN study reported in this article was planned around an existing tutorial structure and content of a 50-minute class aimed at consolidating the key statistical concepts of the normal distribution and sampling distribution of the sample mean, both introduced in a lecture. In the traditional approach, tutors lead the class discussion of a business case study to reinforce the concepts learned in the previous week's lecture. Students participating in the discussion individually answered case-study related questions. At the end of the tutorial, students undertake a quiz which is part of their formative assessment.

The IVN approach followed the process previously practiced in the traditional tutorial settings, however, while the class discussion was still preserved, the case study reinforcing the learned concepts, as well as tutorial exercises, were delivered via the interactive visual narrative.

By following the IVN Learning Design Model (as seen in Figure 1), the learning activity was designed to consist of a series of instructional events (and associated learning outcomes) that were carefully aligned with complementary behavioral processes to support students' cognitive tasks and learning objectives. Students were engaged through the high level of interactivity and visualization, and immersed in a business narrative. The narrative, which ran across all instructional events, centered on the operation of a business that sells music CDs. Our reasoning for this choice was that buying music CDs is an activity that students can easily relate to. Across the entire spectrum of learning activities, students initially undertook analytic tasks related to a simulated brick-and-mortar CD shop (Acme CD, see Figure 2 and Figure 3) and in later weeks the tasks related to a fully operational online store selling music in digital format (Music Mountain, not discussed in this article).

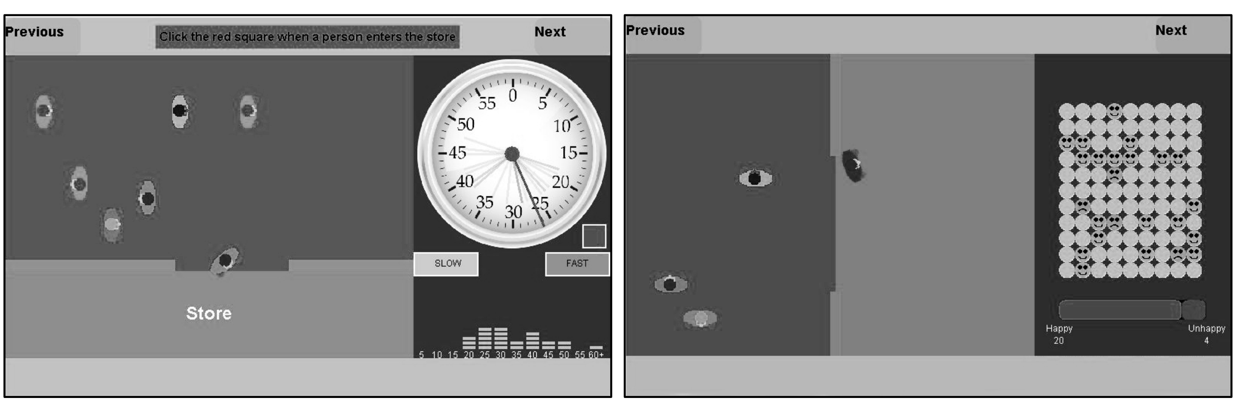


**Figure 2: Data Sampling Tasks**

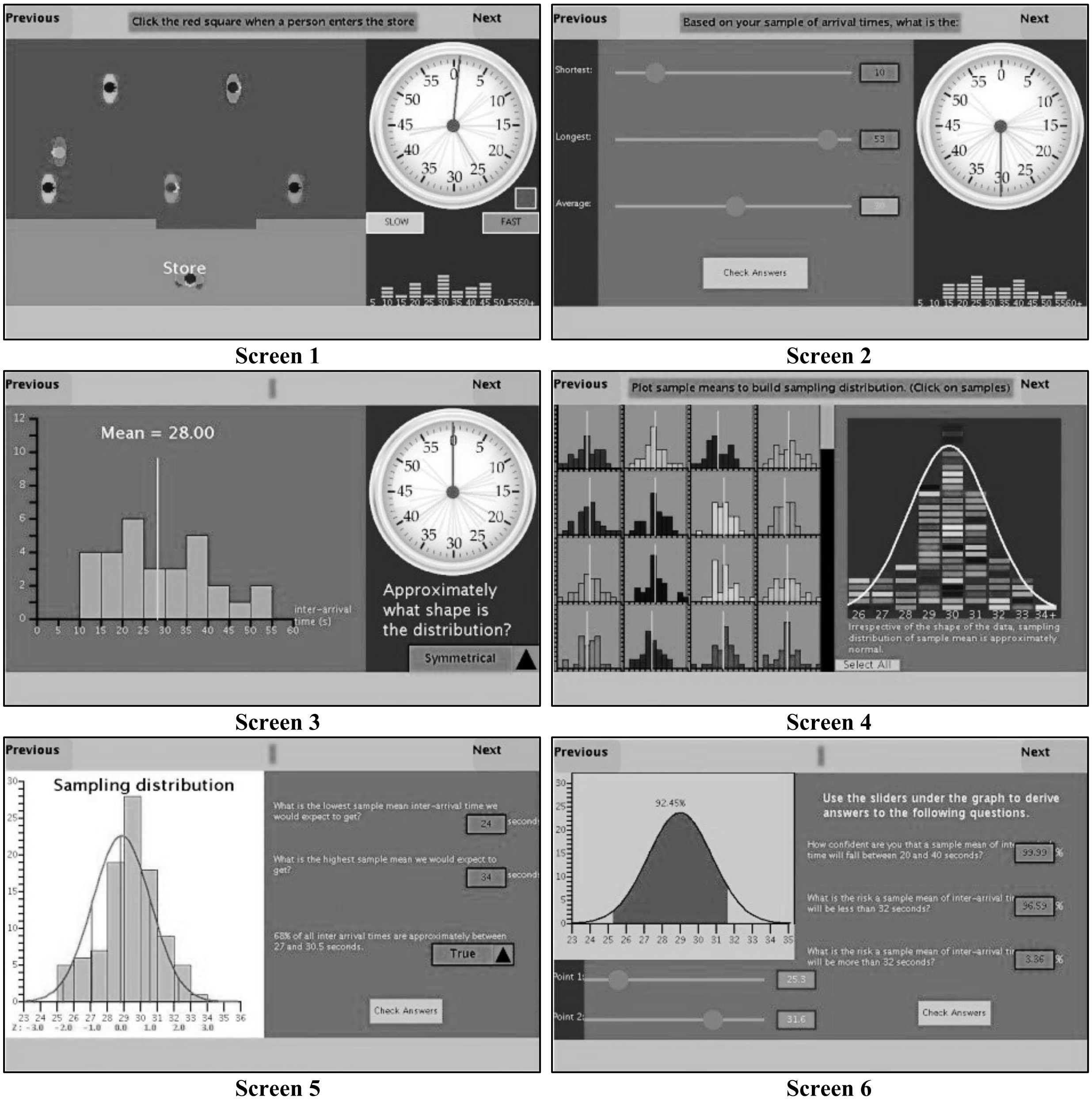


**Figure 3: Interface Design of the IVN Simulator**

The concept of buying music from a shop, whether physical or virtual, can easily be transferred to other business contexts. In their first encounter with the business, the brick-and-mortar CD shop acted as a physical anchor to students for a well-understood shopping activity. We also reasoned that products related to music would be of intrinsic interest to students. For the narrative characters, we used a manager and an assistant to the manager, with the student cast in the role of the assistant. This narrative was used not only to create a setting for the learning activities but also to provide a rich business context for follow-up quiz questions (see Appendix A) which were used to test students' learning of BA concepts. The opening narrative used for the tutorial was:

*Eva, the manager of Acme CD store, is concerned that customers seem to be waiting to be served. She suspects it is because people are coming into the store more frequently than the same time last year and there aren't enough salespeople rostered on.*

Eva then asks the assistant to conduct the necessary data collection by taking a random sample of 30 customer inter-arrival times (the time between successive customer arrivals). This provides the student with the first opportunity for experiential learning in an authentic environment using real tasks. The idea is that the student must monitor the customers entering the store, as simulated on the computer screen, and record the inter-arrival times of the first

31 customers entering the store using a provided (simulated) stopwatch (see Figure 3, Screen 1).

The student action of pressing the stopwatch button is tied to three responses from the system. First, a gray trace line of the second hand position appears on the stopwatch. Second, the inter-arrival time for that customer is recorded. Third, as a means of scaffolding the student's understanding from the concrete representation of the stopwatch to the more abstract concept of a frequency count, a "brick" is also displayed as part of the frequency distribution below the stopwatch (see Figure 3, Screen 1). The stopwatch is then reset. At the end of the data collection the student can intuitively see the distribution of inter-arrival times (as "bricks") and where the majority of inter-arrival times are located on the stopwatch face (as trace lines).

After collecting the sample, the student proceeds to the next screen, where he or she is prompted to answer questions based on observations of the collected data (see Figure 3, Screen 2). The stopwatch and frequency count from the data collection screen is reproduced to facilitate the student's observation. Feedback is provided using a traffic light system (green: correct; yellow: close; red: incorrect).

As the student progresses through the learning activity, the clock and frequency count is replaced with the more abstract representation of a frequency distribution (this represents the concept of "peeling off" the layers of visualization).

After the students understand the shape and nature of the distribution built up from their own data collection (see Figure 3, Screen 3), the next step shows the distribution of the collected data amongst a large number of other distributions previously collected by other data collectors (see Figure 3, Screen 4). As the student selects each distribution, the arithmetic mean of that distribution is visible as one mean amongst many that make up the sampling distribution (see Figure 3, Screens 5 and 6). In this way, the visual elements in concert with the interactive elements and the narrative build the student's understanding of complex abstract statistical concepts by moving from concrete everyday concepts to the more abstract statistical concepts.

| Screen | Learning Objective | Instructional Events | Behavioral Processes | Cognitive Processes |
|---|---|---|---|---|
| 1 | Recognize the difference between a sample and the population. | Students collect a random sample. | Students click on 'people' entering (or leaving) the store to collect a sample. | Association between collecting sample data and the abstraction of a data distribution. Rehearsal also supported as students must do this many times. |
| 2 | Be able to estimate sample statistics from the collected sample. | Students estimate sample statistics for their sample. | Students use sliders to select estimates for the sample statistic. Feedback given when students click 'Check answers' button:<br>• green = correct,<br>• red = incorrect,<br>• yellow = close. | Design supports cognitive organization because students must use the information from the stopwatch and distribution to estimate statistics. |
| 3 | Use knowledge of the shape of data to determine shape of a sample distribution. | Students determine the shape of data they collected. | Select distribution shape from a dropdown list. Color is used to give immediate feedback to students:<br>• green = correct,<br>• red = incorrect,<br>• yellow = close. | Use visual representation of distribution and stopwatch with time imprinted to work out the distribution. |
| 4 | Understand how a sampling distribution is constructed. | Students construct a sampling distribution. | As students click on 'Sampling distribution' (left-hand side), the mean of that sample appears as a matching colored block in the sampling distribution (right-hand side) | Supports organizational and cognitive strategies. Students repeatedly see the connection between selecting a sample mean and its role in building up the sampling distribution. |
| 5 | Use the empirical rule to determine practical range for average inter-arrival times. | Answer questions about average inter-arrival times. | Students answer questions related to the sampling distribution. When button clicked feedback is given:<br>• green = correct,<br>• red = incorrect,<br>• yellow = close. | Distribution of inter-arrival times constructed in the previous screen is overlaid with the theoretical sampling distribution and z-scores. |
| 6 | To determine the probability that a particular sample mean falls between points 'a' and 'b'. | Answer questions about the use of sampling distribution. | Adjust the area under the curve by moving the sliders. | Associate the area under the curve with probability. |

**Table 1: Mapping of Screens in the Learning Activity with the IVN Learning Design Model**

In keeping with the IVN Learning Design Model, each screen was designed to incorporate an instructional event with an aligned learning outcome. The instructional event considered various behavioral processes and was designed to support a range of cognitive processes.

Table 1 describes the entire tutorial task. The overall aim of the task was decomposed into a number of step-wise objectives, which were all planned to directly support the prescribed curriculum of the selected tutorial topic.

The tutorial task was carried out as a series of instructional events (such as students collecting a random data sample), each mapped onto screens and interactions previously discussed and presented in Figure 3. Those screens and interactions (such as the store entrance and a stopwatch) were designed to support some behavioral processes (such as clicking on the stopwatch button or on the icon representing a customer entering a store) and some cognitive processes (such as observing relationships between sampled data and its distribution). Both types of processes had to be facilitated by the IVN environment and students had to be able to accomplish them physically and mentally.

## 4. RESEARCH METHODS

To evaluate the effectiveness of the IVN approach to teaching BA, we conducted a study with a cohort of first-year BA students. At Deakin University (Australia), which hosted this study, Business Analytics is an introductory subject suitable for students without any prior knowledge of statistics, analytics, information management, or business. The course runs for 11 weeks and has a weekly two-hour lecture and one-hour tutorial. Lectures introduce main concepts and subsequent tutorials apply the learned concepts to real-world scenarios. At the start of the term, the university timetable system allocates students to tutorials. In this particular term, we offered 20 tutorials and each had 25 students on average.

To take advantage of the large number of potential student participants, and yet to avoid any negative effect of the study on the curriculum and schedules, we designed an "in-class" study (Alrushiedat and Olfman, 2013; Brown, 1992; Robson, 2011) which was allotted to the sixth week of the tutorial classes. To accommodate the study, we were allowed to update the sixth week's tutorial class materials by incorporating the CD shop case study in the tutorial exercises. We established a baseline understanding in the lecture before the tutorials so that all students started with a comparable level of understanding. Also, tutors recapped the lecture concepts briefly at the beginning of the tutorials. For the study, the research team randomly assigned half of the tutorials (10 tutorial classes) to carry out the traditional method of teaching (denoted as "Traditional") and the other half (10 tutorial classes) to use the Interactive Visual Narrative (denoted as "IVN") method of teaching.

At the end of each tutorial, the participating students completed an in-class quiz, which was part of their formative assessment. The main objective of the quiz was to determine students' understanding of the introduced BA concepts and to compare performance of the two groups in terms of the levels of acquired cognitive skills.

Bloom's taxonomy (1971) allowed us to design a comprehensive educational environment in which to deliver the IVN teaching methods – one that included teaching objectives and learning outcomes, tasks to be undertaken by students, tests and quizzes to be administered, technology to be developed in support of learning tasks, and any other relevant materials.

In the IVN study, the taxonomy also offered guidance as to the design of all quiz questions, which included three multiple-choice questions (Q1, Q2, and Q4 – see Appendix A) and three short-answer questions (Q3, Q5, and Q6).

The questions were formulated by experienced educators (the co-authors of this article) to test the levels of students' cognitive attainment of BA content and to provide a clear link with different levels of Bloom's taxonomy. The quiz was developed collaboratively and mapped against Bloom's taxonomy (1971) and the IVN model of the conducted tasks (refer to Table 1). As each quiz question was designed to correspond to a particular cognitive level of Bloom's taxonomy, a student's ability to answer this question was judged as the attainment of the corresponding cognitive level. The quiz was further refined by feedback from experienced academic staff who were involved in teaching the subject. Table 2 shows a mapping of all quiz questions against different cognitive levels of learning outcomes.

A total of 220 students completed the quiz (119 IVN students and 91 Traditional). Blank responses for quiz questions provided no information regarding students' cognitive processes, however, we analyzed student responses for each question with available information. All quiz responses were graded by an experienced assessor. All assessed responses (with solutions) were returned to

| Cognitive Dimension of Learning Outcome | Quiz Question | Type | Sample Statistics |
|---|---|---|---|
| Knowledge | Q1 | Multiple choice | % students correct |
| | Q2 | Multiple choice | % students correct |
| | Q5 | Short answer | Average grade (Total of 3 points) |
| Analysis | Q3 Part A | Short answer | Average grade (Total of 3 points) |
| Evaluation | Q3 Part B | Short answer | Average grade (Total of 3 points) |
| Comprehension | Q4 | Multiple choice | % students correct |
| Application | Q6 | Short answer | % students able to apply theory into practice |

**Table 2: Quiz Questions vs Cognitive Dimension of Learning Outcomes**

students. All student participants and their tutors checked the results for their consistency and reliability.

## 5. RESULTS FOR LEARNING OUTCOMES AND STUDENT ENGAGEMENT

The students' responses to the quiz were analyzed according to the cognitive dimensions of Bloom's taxonomy, which included students' attainment of Bloom's cognitive "knowledge" (tested in Q1, Q2, and Q5), "analysis" (Q3 Part A), "evaluation" (Q3 Part B), "comprehension" (Q4), and "application" (Q6) levels. To compare students' performance with respect to their knowledge we used a two-proportion Z-test and a two-sample t-test. In order to estimate the true difference between the two groups of students we calculated 95% confidence intervals for items. The results of the inferential statistical analysis are shown in Table 3, and the descriptive statistics themselves are presented in Table 4 (Q1, Q2, Q4, and Q6) and Table 5 (Q3 and Q5).

| Cognitive Dimension of Learning Outcome | Quiz Question | *p* |
|---|---|---|
| Knowledge | Q1 | <0.001 |
| | Q2 | 0.320 |
| | Q5 | 0.003 |
| Analysis | Q3 Part A | <0.001 |
| Evaluation | Q3 Part B | 0.732 |
| Comprehension | Q4 | 0.587 |
| Application | Q6 | 0.033 |

**Table 3: Student Performance on Quiz Questions**

### 5.1 Attainment of Cognitive Level "Knowledge"

Foundation knowledge, or the ability to recall concepts learned in the classroom, was assessed using two multiple-choice questions (Q1 and Q2, see Table 4), and one short-answer question (Q5, see Table 5) worth three points. Q1 assessed the students' ability to recall BA concepts, Q2 assessed the students' ability to recall the relationship between BA concepts, and Q5 assessed the students' ability to describe the process of data analysis.

The analysis of student performance in quiz question one (Q1) showed that around 20% more students in the IVN group were able to better recall BA concepts than their counterparts in the Traditional group. The Z-test for the difference between proportions produced a statistically significant result ($Z = 3.54$, $p < 0.001$, 95% CI [0.08, 0.30]). We estimate that between 8% and 30% more students in the IVN group are able to recall BA concepts than their counterparts in the Traditional group. However, for quiz question two (Q2), the IVN group only marginally (4%) outperformed their peers in the Traditional group when recalling the relationship between BA concepts. The Z-test confirmed that this difference was not statistically significant ($Z = 0.99$, $p = 0.320$, 95% CI [–0.03, 0.11]).

For quiz question five (Q5), the IVN students scored 0.3 points more on average than the students in the Traditional group in describing this step of the analysis. A closer look at the descriptive statistics for Q5 (see Table 5) shows that half the students who attended the IVN tutorial scored more than 33% of the available points, compared to 17% in the Traditional tutorial. Though seven students from the IVN tutorial scored very high grades, the dispersion of data was similar in both groups.

| | Q1 | | Q2 | | Q4 | | Q6 | |
|---|---|---|---|---|---|---|---|---|
| | **Traditional** | **IVN** | **Traditional** | **IVN** | **Traditional** | **IVN** | **Traditional** | **IVN** |
| Attempted (N) | 91 | 119 | 91 | 119 | 91 | 119 | 91 | 119 |
| Returned (n) | 87 | 117 | 84 | 118 | 74 | 110 | 90 | 119 |
| Response Rate | 96% | 98% | 92% | 99% | 81% | 92% | 99% | 100% |
| Successful | 69% | 89% | 89% | 93% | 51% | 47% | 28% | 42% |

**Table 4: Descriptive Statistics for Q1, Q2, Q4, and Q6 (questions which were marked as "correct" or "incorrect")**

| | Q3A | | Q3B | | Q5 | |
|---|---|---|---|---|---|---|
| | **Traditional** | **IVN** | **Traditional** | **IVN** | **Traditional** | **IVN** |
| Attempted (N) | 91 | 119 | 91 | 119 | 91 | 119 |
| Returned (n) | 68 | 103 | 68 | 105 | 42 | 69 |
| Response Rate | 75% | 87% | 75% | 88% | 46% | 58% |
| Mean (M) | 0.62 | 1.16 | 0.70 | 0.68 | 0.62 | 0.92 |
| Median | 0.50 | 1.00 | 0.50 | 0.50 | 0.50 | 1.00 |
| SD | 0.65 | 0.72 | 0.39 | 0.51 | 0.40 | 0.57 |
| $25^{th}$ percentile | 0.0 | 0.5 | 0.5 | 0.5 | 0.5 | 0.5 |
| $75^{th}$ percentile | 1.0 | 2.0 | 1.0 | 1.0 | 1.0 | 1.0 |
| Maximum points | 2.0 | 2.5 | 2.0 | 3.0 | 1.5 | 2.5 |
| Minimum points | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 | 0.0 |

**Table 5: Descriptive Statistics for Q3A, Q3B, and Q5 (questions which were marked up to 3 points)**

A two-sample t-test indicated that the difference between the two average scores was significant (t (106) = 3.27, p = 0.003, 95% CI [0.10, 0.50]). Moreover, a 95% confidence interval calculation showed that the average score for students in the IVN tutorial was greater than the average score for students in the Traditional tutorial by between 0.10 and 0.50 points.

The analysis of students' answers to questions one, two, and five revealed that at Bloom's "knowledge" level, in general, the IVN tutorial method helped students to grasp BA concepts better than the traditional method.

### 5.2 Attainment of Cognitive Level "Analysis"

Question 3 Part A tested the students' ability to break down a concept into its components and reason about their mutual relationship. The summary statistics (see Table 5) showed that, in general, students from the IVN tutorials attained more points as compared with their counterparts in the Traditional tutorials. In fact, 50% of the students from the IVN tutorials scored between 1.0 and 2.5 points, whereas the score of the top 25% of students from the Traditional tutorials ranged from 1.0 to 2.0 points, and the bottom 25% of students did not obtain any points. Additionally, the IVN-tutorial students' scores were more spread out: the middle 50% of the score range from 0.5 to 2.0 points, compared to 0.0 to 1.0 points in the Traditional tutorials. The two-sample t-test confirmed that the difference is significant between the two groups for attainment of Bloom's "analysis" level of learning (t (169) = 4.97, p < 0.001, CI 95% [0.32, 0.75]). In fact, we are 95% confident that the average score of the IVN students are likely to be 0.32 to 0.75 points greater than that of students in the traditional tutorials.

### 5.3 Attainment of Cognitive Level "Evaluation"

Question 3 Part B focused on testing the students' ability to make informed judgements about the solutions of their analysis. Though the mean score for this quiz question was slightly higher for the students in the Traditional tutorials as compared with the students in the IVN tutorials (see Table 5), there was no discernible difference between the two distributions of scores. Note that four students from the IVN tutorials attained very high scores compared to just one student from the Traditional tutorials. Furthermore, the difference between the mean scores of the two tutorial groups was non-significant (t (171) = 0.2576, p = 0.732, CI 95% [–0.16, 0.12]), indicating that the two groups had similar learning outcomes for Bloom's "evaluation" level of learning.

### 5.4 Attainment of Cognitive Level "Comprehension"

Students' levels of comprehension were assessed with a multiple-choice question, Q4. A little over half of the students (51.35%) from the Traditional tutorial who attempted the question were successful in identifying the correct solution; similarly, nearly half (47.27%) of the students from the IVN tutorial were successful in identifying the correct solution. Not surprisingly, this difference of approximately 4% in ability to comprehend BA concepts was not statistically significant (Z = 0.5427, p = 0.587, 95% CI [–0.18, 0.10]).

### 5.5 Attainment of Cognitive Level "Application"

The sixth quiz question, Q6, required a short answer and was constructed to assess students' ability to use the concepts they had previously learned in class in an entirely new context. The data showed that 15% more students in the IVN tutorial group successfully demonstrated that they could apply the concepts learned in class to a new situation, compared to their peers in the Traditional group. The Z-test confirmed that there is a significant difference between the two groups (Z = 2.1250, p = 0.033, 95% CI [0.01, 0.27]). We can conclude that at Bloom's "application" level, students from the IVN tutorials performed better than their counterparts in the Traditional tutorials. More precisely, between 1% and 27% more students in the IVN group are able to apply BA concepts to a new context than their counterparts in the Traditional tutorial group.

### 5.6 Analysis of Student Engagement

After completing the quiz, participants were also asked to indicate their level of engagement in the tutorial tasks, which was measured based on their responses to five extra questions (E1 to E5; see Figure 4). The answers represented their negative or positive attitudes to the tutorial methods and the process followed and were recorded in a range from 1 (strong disagreement with the prompting statement) to 7 (strong agreement with the prompting statement).

Our analysis of students' responses relied on the Net Promoter Score (NPS) (Reichheld, 2003), a descriptive technique that measures participants' overall experience, which is not specifically linked with quality, satisfaction, or value but which, in disciplines such as Marketing, is considered as evidence of improvement and growth due to the power of word of mouth (Keiningham et al., 2008). When using NPS, the participant responses – both negative and positive, often to a single question – are categorized into three distinct groups: promoters (those with positive attitude), passives, and detractors (those with negative attitude). The NPS approach is to periodically measure the customers' overall experience and shape the strategy based on methods of converting detractors into promoters. In this study, by applying the NPS guidelines, we categorized our students in respect of each of our quiz questions E1 to E5 as follows:

- **Promoters** (participants giving a score between 5 and 7): positive and enthusiastic
- **Passives** (participants giving a score of 4): satisfied but unenthusiastic
- **Detractors** (participants giving a score between 1 and 3): unhappy and negative.

The final NPS value measures student overall experience and is given as a number between –100 and +100 to denote the difference between the percentage of promoters and detractors. Positive and high NPS values in IVN tutorials for four out of five questions (E1, E2, E3, and E5) and a high NPS value in Traditional tutorials for the negatively formulated question (E4) demonstrated that IVN students had positive experiences in the tutorials compared to their counterparts in the Traditional tutorials (see Figure 4).

E1: I enjoyed the tutorial

| | Detractors (1–3) | Promoters (5–7) | NPS |
|---|---|---|---|
| **IVN** (114) | 11.40% (13) | 70.18% (80) | 59 |
| **Traditional** (80) | 17.50% (14) | 58.75% (47) | 41 |
| ***p*** | 0.227 | 0.099 | |

E2: There was enough time to complete the tutorial

| | Detractors (1–3) | Promoters (5–7) | NPS |
|---|---|---|---|
| **IVN** (114) | 14.04% (16) | 70.18% (80) | 56 |
| **Traditional** (80) | 32.50% (26) | 52.50% (42) | 20 |
| ***p*** | 0.002 | 0.012 | |

E3: The tutorial helped me understand the concepts

| | Detractors (1–3) | Promoters (5–7) | NPS |
|---|---|---|---|
| **IVN** (114) | 11.40% (13) | 71.93% (82) | 61 |
| **Traditional** (80) | 18.75% (15) | 63.75% (51) | 45 |
| ***p*** | 0.151 | 0.227 | |

E4: The tutorial (task) was challenging (difficult)

| | Detractors (1–3) | Promoters (5–7) | NPS |
|---|---|---|---|
| **IVN** (114) | 14.91% (17) | 61.40% (70) | 46 |
| **Traditional** (80) | 10.00% (8) | 76.25% (61) | 66 |
| ***p*** | 0.314 | 0.029 | |

E5: The tutorial instructions were easy to understand

| | Detractors (1–3) | Promoters (5–7) | NPS |
|---|---|---|---|
| **IVN** (114) | 7.89% (9) | 78.95% (90) | 71 |
| **Traditional** (80) | 23.75% (19) | 56.25% (45) | 32 |
| ***p*** | 0.002 | <0.001 | |

**Figure 4: Comparison of Student Engagement in Tutorials Using NPS**

We compared the percentages of promoters and detractors in both the Traditional and IVN tutorial groups using Z Test for the difference between two proportions. This was done to determine what kind of student experience could best explain the difference in the NPS value between the two tutorial groups. When the difference between IVN and Traditional groups of promoters or detractors is significant (as indicated by the p-value obtained from a Z test), then we can claim that the difference in NPS values can be attributed to the promoters' positive views or detractors' negative views (or both). When such significance cannot be demonstrated, then the dissimilarity of NPS values indicates merely the potential for improvement but which cannot be easily explained at this point in time.

When assessing whether students enjoyed the tutorial (E1), even though the IVN group had lower detractors and higher promoters than the Traditional tutorial group, the differences for detractors ($Z = -1.2$, $p = 0.227$, 95% CI [–0.15, 0.03]) and promoters between the two tutorial groups ($Z = 1.64$, $p = 0.099$, 95% CI [–0.02, 0.25]) were not statistically significant at 5% level of significance. We therefore cannot attribute the difference in NPS scores to the views of either the group of promoters nor detractors.

The IVN students felt that they had enough time to complete the tutorial (E2) as the IVN group had both more promoters and less detractors within their group compared to the Traditional tutorial group. The differences for detractors ($Z = -3.00$, $p = 0.002$, 95% CI [–0.30, -0.06]) and promoters between the two tutorial groups ($Z = 2.50$, $p = 0.012$, 95% CI [0.03, 0.31]) were statistically significant, thus indicating that the views of both promoters and detractors were clearly polarized and thus had a significant impact on the NPS measure.

A similar pattern where the IVN group had both more promoters and less detractors within their group as compared to the Traditional tutorial group was also evident when asked whether the tutorial was helpful in understanding the concepts taught in the class (E3). However, the differences for detractors ($Z = -1.43$, $p = 0.151$, 95% CI [–0.17, 0.02]) and promoters ($Z = 1.20$, $p = 0.227$, 95% CI [–0.05, 0.21]) were not statistically significant, and while the NPS score was indicative of a positive trend, it cannot be explained at this point in time and should be followed up in the future.

When it came to challenges (difficulties) posed by the tutorial tasks (E4), in this negatively formulated question there were more promoters and less detractors in the Traditional tutorials than the IVN tutorials. The difference between promoters of the two tutorial group was significant ($Z = -1.17$, $p = 0.029$, 95% CI [–0.28, -0.01]) and the difference between two detractors was not statistically significant ($Z = -1.43$, $p = 0.151$, 95% CI [–0.04, 0.14]). It was, therefore, the views of the promoters that were responsible for the difference in the NPS measure, and thus more hardship experienced in the traditional delivery of tutorials.

IVN students also found the tutorial instructions were easy to understand as there were more promoters and less detractors in the IVN group compared to the Traditional group. The difference for detractors ($Z = -3.00$, $p = 0.002$, 95% CI [–0.25, –0.05]) and the difference for promoters ($Z = 3.38$, $p = 0.000$, 95% CI [0.09, 0.35]) were statistically significant, thus indicating that the views of both promoters and detractors had a significant impact on the NPS measure.

## 6. DISCUSSION

The results of the study suggest that the IVN approach, as compared with traditional teaching methods, had a significant positive effect on student learning outcomes and engagement. In particular, a comparison of attaining cognitive skills between the two groups of students showed that the IVN approach was more effective in enhancing and facilitating the learning and recall of new concepts and techniques; more effective for the application of newly learned analytical methods in new situations; and more useful for the ability to analyze and reason about new problems and their analytic solutions (“knowledge,” “application,” and “analysis,” respectively, as per Bloom’s taxonomy). On the other hand, there was insufficient evidence to suggest that there was a difference in the effectiveness of the two methods in facilitating students’ “comprehension” and “evaluation” skills. It is important to note that the high level of difficulty associated with these two objective assessment items may have influenced the outcome (in Q4 neither group scored more than 50%, and in Q3 Part B the performance of both groups was below par: the average score was 0.70 out total of 3 points for the IVN group and 0.68 for the Traditional group). Finally, the IVN approach was also perceived by students as helpful in understanding difficult concepts, and making them easier and quicker to understand; it was also perceived as more enjoyable and less challenging than the traditional methods of teaching.

Our study extends previous work that used data visualization, interactivity, and narratives to teach abstract and challenging curricula (c.f., Brodbeck, Mazza, and Lalanne 2009; Domagk, Schwartz, and Plass 2010; Kennedy 2004; McCarthy 2012; Yarden and Yarden 2010). We have shown in this study that clearly aligned learning activities infused with IVN elements lead to better learning outcomes and higher student engagement. Our findings are contrary to Novak’s (2014) study, which suggested a negligent effect of narratives on learning outcomes and student engagement. The reasons for these different outcomes could be attributed to differences in cohort (Novak studied graduate students whereas our study was based on undergraduate students) or to different research approaches. Regardless, the contrary outcomes highlight the need for more research in this area.

Of pivotal importance to this research project was its methodological framing, encapsulated in the adopted IVN Learning Design Model (see Figure 1). The model was used to design the curriculum, tools, and activities that could emphasize the role of interactivity, visualization, and narrative in learning. In line with the model’s recommendations, all activities, supporting tools, and environments had to provide clear links to learning objectives and outcomes, as well as elements of student engagement, which in tandem were capable of motivating and stimulating learners’ cognitive and behavioral processes via a collection of well-designed instructional events (see Table 1).

A research instrument – the quiz, which was used also as part of formative assessment – was designed with the aid of Bloom’s taxonomy (1971) and adapted to studying the level of student attainment of the IVN-assisted learning outcomes (see Table 2). As implied by the IVN model, the research instruments were further enhanced in order to allow the investigation of student engagement and the resulting motivational factors (see Figure 4). We believe that the IVN Learning Design Model is eminently suited as a design tool to develop abstract and challenging types of curricula such as BA, and that such curricula are capable of overcoming well-known teaching challenges (associated with difficult subject matter) and will engage students in exciting and rewarding learning activities.

Our experiences in developing learning activities also provide several insights to practitioners. Foremost, in order to address the challenge of students’ aversion to the abstract and mathematical nature of the BA content, as well as their lack of prior business experience, it is important to design business narratives that are suitable for the level of understanding of a typical first-year Information Systems and Business student. It is also important to make these narratives engaging and authentic, with believable characters, responsibilities, and actions to which students can easily relate and which they could readily adopt in simulated cases and environments. However, care must be taken to keep the complexity of the narrative to a minimum so it does not add to students’ cognitive load, which may already be significant due to a complex curriculum. Another reason to keep the narrative simple is that it should not be a hindrance to overseas students with English as their second language.

While the narrative provides the overall framework to anchor the learning activity, the data visualization reduces data complexity and enhances students’ comprehension of data and analytic methods, which was shown to assist in recalling information easily. The interactive components of visualizations promote direct manipulation of data and analytic tools, and in this way encourage students' experiential learning. Interactions often reflect the cause and effect of analytic actions, which was important to facilitate learning, and equally importantly, to contextualize this learning in business circumstances. Interactive visualizations also assist students with their problem-solving skills, and guide them along the analytic process in problem decomposition and in seeking data-based solutions.

At the same time, our study has limitations. The main limitation stems from a predetermined curriculum and university processes in a live in-class environment, which is common in educational research (Brown, 1992) but which prevents application of typical controls used in laboratory experiments (Brown, 1992; Collins, Joseph, and Bielaczyc, 2004). For example, it was not possible to conduct pre- and post-tests without altering the subject assessment regime; we could not avoid voluntary participation due to the stringent ethical constraints; we could not ensure a fixed number of students in each group as this was determined by enrollment and attendance; and we only had one chance to carry out the study and no opportunities to repeat the study without disrupting the natural flow of the teaching schedule. However, we could in turn argue that lessons learned from real-world scenarios rather than laboratory experiments make it easier to generalize to other real students in real courses (Hosack, Lim, and Vogt, 2012).

Finally, it should be noted that response rates for both the Traditional and IVN groups were similar and were also relatively high for all questions (between 75% and 100%), except for question Q5 (Traditional 46% vs. IVN 58%). The issue of response rate was directly related to the adopted method of treating blank responses to quiz questions, which were considered as invalid and discarded rather than valid but incorrect. However, as the IVN groups always had a higher response rate – either due to the students' higher engagement or better cognitive attainment – and since they were generally better than those obtained from the Traditional groups, treating blank responses as invalid rather than incorrect provided a more conservative assessment of the obtained results.

## 7. CONCLUSIONS

This article reported the use of interactive visualizations and narratives to teach foundations of BA concepts, such as data analysis and statistics, to first-year undergraduate students, and the results of these classroom interventions. One way to measure the efficacy of a new, innovative teaching method is to compare learning outcomes for students who used the new method (in this case, IVN) against a "Traditional" method. For this research, a two-sample hypothesis test on the in-class quiz developed for the study found statistical significant results in Bloom's "knowledge," "analysis," and "application" levels but no statistically significant difference in "evaluation" and "comprehension" levels. Another way to assess the efficacy of the IVN approach is to assess student perceptions of the learning activities. An in-class survey constructed for this purpose indicated that a majority of students enjoyed the IVN tutorials. However, the differences between the IVN and Traditional teaching methods were not always statistically significant. These mixed findings suggest the need for further empirical work in a more controlled environment to identify the exact circumstances under which IVN methods lead to better learning outcomes and student engagement. To this end, this and our future studies include the design and evaluation of new learning activities, tools, and materials, all useful in teaching and learning BA in both university and professional education settings.

In conclusion, the reported study demonstrates the possibility of using interactive visual narratives (IVN) to teach difficult subject matter. Our results suggest that a combination of interactive visualizations and narratives can improve the acquisition of data analysis (or other difficult) knowledge, facilitate essential skills in problem analysis and the application of solutions, and enhance student engagement. As such, by designing curricula to take advantage of interactive visualizations and narratives, we may well be teaching students, who are predominantly intuitive thinkers, to become better analytical thinkers – the very skill that they will need in their future careers as business analysts.

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## 9. REFERENCES

Alrushiedat, N. & Olfman, L. (2013). Aiding Participation and Engagement in a Blended Learning Environment. *Journal of Information Systems Education*, 24(2), 133–145.

Bloom, B., Engelhart, M., Furst, E. J., Hill, W. H., & Krathwohl, D. R. (1956). *Taxonomy of Educational Objectives : The Classification of Educational Goals. Handbook I: Cognitive Domain*. London, UK: Longmans.

Bloom, B., Hastings, T., & Madaus, G. F. (1971). *Handbook of Summative and Formative Evaluation of Student Learning*. New York, NY: McGraw-Hill.

Brodbeck, D., Mazza, R., & Lalanne, D. (2009). Interactive Visualization - A Survey. In D. Lalanne & J. Kohlas (Eds.), *Human Machine Interaction* (27–46). Springer Berlin Heidelberg.

Brown, A. L. (1992). Design Experiments: Theoretical and Methodological Challenges in Creating Complex Interventions in Classroom Settings. *Journal of the Learning Sciences*, 2(2), 141–178.

Bruner, J. (2002). *Making Stories*. New York, NY: Farrar, Strauss, and Giroux.

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

Collins, A., Joseph, D., & Bielaczyc, K. (2004). Design Research: Theoretical and Methodological Issues. *Journal of the Learning Sciences*, 13(1), 15–42.

Cybulski, J. L., Keller, S., & Saundage, D. (2015). Interactive Exploration of Data with Visual Metaphors. International. *Journal of Software Engineering and Knowledge Engineering*, 25(2), 231–252.

Domagk, S., Schwartz, R. N., & Plass, J. L. (2010). Interactivity in Multimedia Learning: An Integrated Model. *Computers in Human Behavior*, 26(5), 1024–1033.

Gagné, R. M. (1977). *The Conditions of Learning (3rd ed.)*. New York, NY: Holt, Rinehart and Winston.

Gartner. (2012). Mobility and Business Intelligence Top Technology Priority List for Australian and New Zealand CIOs in 2012. Retrieved April 30, 2014, from http://www.gartner.com/newsroom/id/1973815.

Harmer, B. M. (2009). Teaching in a Contextual Vacuum: Lack of Prior Workplace Knowledge as a Barrier to Sensemaking in the Learning and Teaching of Business Courses. *Innovations in Education and Teaching International*, 46(1), 41–50.

Heer, J., Bostock, M., & Ogievetsky, V. (2010). A Tour through the Visualization Zoo. *Communications of the ACM*, 53(6), 59–67.

Hosack, B., Lim, B., & Vogt, W. P. (2012). Increasing Student Performance through the Use of Web Services in Introductory Programming Classrooms: Results from a Series of Quasi-Experiments. *Journal of Information Systems Education*, 23(4), 373–383.

Keim, D., Andrienko, G., Fekete, J. D., Görg, C., Kohlhammer, J., & Melancon, G. (2008). Visual Analytics: Definition, Process, and Challenges. In A. Kerren, J. T. Stasko, J.-D. Fekete, & Chris North (Eds.), *Information Visualization: Human-Centered Issues and Perspectives* (154–175). Springer.

Keiningham, T. L., Aksoy, L., Cooil, B., & Andreassen, T. W. (2008). Linking Customer Loyalty to Growth. *MIT Sloan Management Review*, 49(4), 51–57.

Kennedy, G. (2004). Promoting Cognition in Multimedia Interactivity Research. *Journal of Interactive Learning Research*, 15(1), 43–61.

Krathwohl, D. R. (2002). A Revision of Bloom's Taxonomy: An Overview. *Theory into Practice*, 41(4), 212–218.

Manyika, J., Chui, M., Brown, B., Bughin, J., Dobbs, R., Roxburgh, C., & Byers, A. H. (2011). *Big Data: The Next Frontier for Innovation, Competition, and Productivity*. McKinsey Global Institute.

McCarthy, M. (2012). Applying Narrative to the Delivery of the Ill-Defined Domain of Manufacturing Systems to Undergraduate Students. *Australasian Journal of Engineering Education*, 18(1), 49–59.

Murtonen, M. & Lehtinen, E. (2003). Difficulties Experienced by Education and Sociology Students in Quantitative Methods Courses. *Studies in Higher Education*, 28(2), 171–185.

Mvududu, N. (2003). A Cross-Cultural Study of the Connection Between Students' Attitudes Toward Statistics and the Use of Constructivist Strategies in the Course. *Journal of Statistics Education*, 11(3).

Novak, E. (2014). Effects of Simulation-Based Learning on Students' Statistical Factual, Conceptual and Application Knowledge. *Journal of Computer Assisted Learning*, 30(2), 148–158.

Polkinghorne, D. E. (1988). *Narrative Knowing and the Human Sciences*. Albany, NY: SUNY Press.

Prabhakar, G. P. (2008). Stats for the Terrified: Impact of Different Teaching and Learning Approaches in the Study of Business Statistics. *International Journal of Business and Management*, 3(6), 21–28.

Reichheld, F. F. (2003). The One Number you Need to Grow. *Harvard Business Review*, 81(12), 46–55.

Renkl, A. & Atkinson, R. K. (2007). Interactive Learning Environments: Contemporary Issues and Trends. An Introduction to the Special Issue. *Educational Psychology Review*, 19(3), 235–238.

Robson, C. (2011). *Real World Research: A Resource for Users of Social Research Methods in Applied Settings (3rd ed.)*. Chichester, UK: Wiley.

Rossiter, M. (2002). Narrative and Stories in Adult Teaching and Learning. *ERIC Clearinghouse on Adult Career and Vocational Education*. Retrieved from http://files.eric.ed.gov/fulltext/ED473147.pdf.

Russom, P. (2011). Big Data Analytics (TDWI Best Practices Report). *The Data Warehousing Institute*. Retrieved from http://tdwi.org/research/2011/09/best-practices-report-q4-big-data-analytics/asset.aspx?tc=assetpg.

Schroeck, M., Shockley, R., Smart, J., Romero-Morales, D., & Tufano, P. (2012). Analytics: The Real-World Use of Big Data: How Innovative Enterprises Extract Value from Uncertain Data. *IBM Institute for Business Value*. Retrieved from http://www-935.ibm.com/services/us/gbs/thoughtleadership/ibv-big-data-at-work.html.

Stubbs, E. (2015). IAPA Skills and Salary Survey (Survey). *Institute of Analytics Professionals of Australia*. Retrieved from http://www.iapa.org.au/Article/2015IAPASkillsSalaryReport

Ware, C. (2012). *Information Visualization: Perception for Design (3rd ed.)*. Morgan Kaufmann.

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

Yarden, H. & Yarden, A. (2010). Learning Using Dynamic and Static Visualizations: Students' Comprehension, Prior Knowledge and Conceptual Status of a Biotechnological Method. *Research in Science Education*, 40(3), 375–402.

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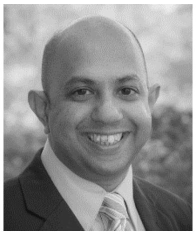

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## Appendix A: In-Class Quiz

Answer the following questions about sampling distribution

Q1) The shape of the sampling distribution tends to be
- a) Negatively Skewed
- b) Bimodal
- c) Positively Skewed
- d) Normal

Q2) If you have a negative z-score it will be:
- a) Above the mean
- b) On the mean
- c) Below the mean
- d) Is not related to the mean at all

Q3) Jill took a random sample of 30 people and found the average money spent on CDs was $25 a month. James also took a random sample of 30 and found the average to be $27 per month. The manager took his own random sample of 30 and found the average to $35 per month.
- a) Assuming that all three samples were taken in the same way, why do you think the manager's average is so different from the others?

  | … |
  |---|

- b) The manager needs to make a business decision based on the average spending of all customers. Can she use $35 as the true average of all customers? Explain your answer.

  | … |
  |---|

Q4) The sampling distribution refers to:
- a) the distribution of the various sample sizes which might be used in a given study
- b) the distribution of the different possible values of the sample mean together with their respective probabilities of occurrence
- c) the distribution of the values of the items in the population
- d) the distribution of the values of the items actually selected in a given sample
- e) none of the above

Q5) Briefly describe how to construct a sampling distribution of average money spend on CDs per month.

| … |
|---|

Q6) Where else could you apply the statistical concepts you learned in this tutorial?

| … |
|---|

Questions measuring engagement are shown in Figure 4.

## Appendix B: Grading criteria for the quiz

All multiple-choice questions were treated as either correct or incorrect and all short-answer question were graded with maximum 3 points. For Question 3 Part A, students could get up to 3 points for recognizing and articulating that each sample yields different sample statistics. For Question 3 Part B, students needed to mention about sample statistics being only a point estimate of the population parameter to receive up to 3 points. Students could get up to 3 points for Q5 for accurately describing the sequence of constructing a sampling distribution, and up to 3 points for providing an example of an application of statistical concepts to another context.

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