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Review Article

Introducing Business Visual Analytics into Business Education by Information Technology and Computing Methods

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Business students feel an urgency to be competent involving business intelligence in their studies and career. This study examines the current literature on business visual analytic technologies (VATs), both in the business community and in business learning, and points out consideration as a research gap in the existing literature. We conduct a systematic review with database searches from 2006 to 2020. The objectives of the review are to identify (a). the existing terminologies related to VATs in the literature; (b). the purpose of VAT application and the benefits of VATs in the business community; and to examine (c). how the VATs are related to the educational context, particularly, in business learning. The findings indicate that VATs provide positive enhancement in business analytics; however, the effect of VAT application in business learning is rather limited. We provide insights for further studies involving VAT-enhanced business learning.

1. Introduction

In recent years, the interest in big data analytics receives considerable attention and enthusiasm from the business community since it is widely applied in a variety of business functions such as predicting future trends and aiding decision-making to create business value [1]. As an emergent field mostly explored in business intelligence, big data analytics refers to utilizing analytic methods to deal with the variation of big data for actionable descriptive, predictive, and prescriptive results [2]. With such approaches, decision-makers can integrate the wisdom created via technologies into their strategies to precisely generate competitive business value [3].

By responding to the need of improving data analytic competencies in the business field, the Association to Advanced Collegiate Schools of Business (AACSB) international is currently encouraging big data analytic education and this leads to most universities seek to include data analytics into the business curriculum [4]. For example, Zhao and Zhao, S. [5] explored that 68.80% among 215 ACCSB-accredited business schools launch business data analytic programs at varied academic levels (i.e., Bachelor's, Master's, MBA, and PhD) to prepare students to satisfy the market needs for business analytic professionals. Wilder and Ozgur [6] designed the business analytic curriculum for undergraduate students. They indicate that business analytic curriculum should include data management, data visualization, and descriptive, predictive, and prescriptive analytics. However, while universities are aware to launch business (data) analytic majors, it is critical to recognize that data analytic knowledge in business school should be equipped in a variety of disciplines across accounting, marketing, application development, financial engineering, and healthcare administration [7, 8]. Business professionals who are not majoring in data analytics should be able to utilize data analytic techniques in their professional functions. In other words, business students are required to have business analytic competent to advance their academic fields and successfully compete in an increasing complex and data-driven world. Indeed, how to appropriately integrate business analytics in the course for students who are not specialized on data analytics presents a challenge. This is because (1) limited amount of credit hour restricts additional data analytic courses on an already crowded undergraduate curriculum [4]. (2). How analytic insights transform into valuable knowledge still remains unexplored [9]. (3) Most studies have primarily emphasized on big data infrastructure intelligence, and other resources like human knowledge or business analytic competencies have been overlooked [3]. As a result, the opportunity of how people incorporate data analytic technology into strategic thinking remains underdeveloped [10]. Therefore, it is important to understand how to proceed a business analytic learning activity in classroom for undergraduate students who are not majoring in data analytics but in the fields across business such as accounting, marketing, management, and finance. To this aim, course offering with a focus on applying analytic technology at the undergraduate level seems to be a concern [11]. In recent years, to address the challenges of big data, visual analytic technologies (VATs), with data mining algorithm over unstructured data source, are introduced to the business community for predicting behaviors, consumption patterns, consumer insight, and other related operations through a faster visual understanding. To explore these VATs' value in business learning, this study aims to conduct a literature review to provide an arch to support the necessary attention of VATs with its potential application in business learning. It contributes to give insights for educator in that VATs may provide the data analytic competence for students who are not majoring in data analytics but required to make decision with business intelligence. Meanwhile, it also brings a new direction in bridging the gap between the flood VATs in the business community and the poor VAT application in business learning. Hence, the findings of this study could be useful for the modification of business curriculum in higher education to better align with current industrial needs.

This study is structured as follows. In section 2, we conceptualize the VATs and classify the dimensions of business analytics to specify our review on the application of VATs in the business community. In section 3, we illustrate the research methodology of developing a literature review following research questions. In section 4, we proceed to the findings on the systematic review. In sections 5 and 6, we make a discussion and outline a series of areas that are currently underdeveloped issues in business learning. In closing, section 7 presents concluding remarks and limitations on this study.

2. Related Literature

2.1. Conceptualizing the Visual Analytic Technologies. Since the mid-2010s, a variety of machine learning was developed in the field of visual analytics for effectively linking data mining algorithms with interactive visual interface to explore, understand, and interact with big data [12]. Interactive visual interface provides opportunity for end users to engage in self-service business analytics. Based on Perdana et al. [13]'s classification concerning to visualization science, four terminologies (i.e., visual analytics, information visualization, scientific visualization, and interactive data visualization) serve as the same purpose of enabling users to explore insight and make decision with analytical visualization. In this study, our researchers define visual analytical technologies (VATs) as a board term including these four terminologies. Thus, serving as the same purpose of insight exploration, they enjoy the common features of interactivity and visual representation that provide potential for analytical reasoning [14].

2.2. Identifying Business Analytics. Delen and Demirkan [15] propose three types of business analytics, namely, descriptive, predictive, and prescriptive analytics. They explain business analytics as a service that is a more or less new concept in business context. These analytic-oriented concepts facilitate the fulfillment of business objectives through analyzing a huge volume of data to describe development, generating predictive models to foresee future opportunities or optimize organizational performance. As indicated in Figure 1, descriptive analytics uses the data to report simple periodic, on-demanding business performance. It is also called business reporting with the output of descriptive identification of business challenges and opportunities. Predictive analytics applies data to discover exploratory or predictive trend, which represents the relationships between inputs and outputs and forecasts future movement. Prescriptive analytics utilizes data to model and optimize performance. It requires users to have upper-level business skills and interdisciplinary abilities in regard to foundational business, accounting, and board management competencies to present storytelling [16]. It is noted that all these three types of analytics constitute today's business analytics when facing big data analytics.

2.3. Infusing Visual Analytic Technologies into Business Analytics. According to the information technology and computing methods, VAT merges data mining techniques with visualization modeling to provide actionable knowledge. VATs allow decision-makers to gain an understanding of past performance, to predict the future trends, and to model the likelihood of decision outcomes. These technologies can help provide insights for users to make decision in terms of different business environment. On the other hand, the three types of business analytics play its role in business intelligence. Therefore, this study subsequently makes a literature review on how these four visualization technologies related to different types of business analytics to discover the potential of VATs in the business community.

3. Research Methodology

Following the practical guide of Petticrew and Roberts [17], we systematically collect and analyze the current issues on VATs in business application and business learning. We conduct the review with four distinct stages. First, we define the boundaries and raise the research questions; second, we develop interdisciplinary group of experts to define the criteria of inclusion and exclusion for reducing bias; third, we undertake an in-depth content analysis to perform a quality check; fourth, we finalize the review through data

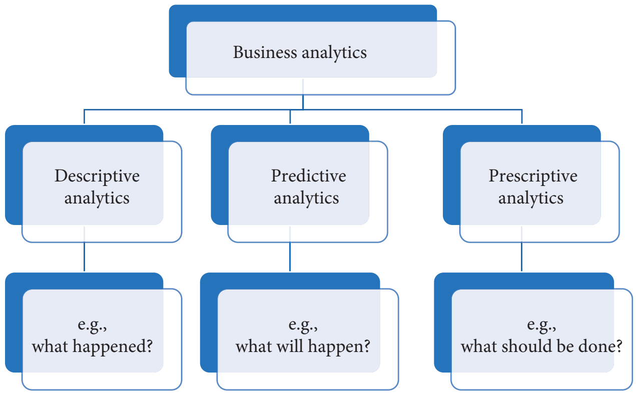

Figure 1: A simple taxonomy of business analytics (source: [15]).

extraction, critical appraisal, and evidence synthesis to answer the specific research questions.

3.1. Defining the Question. This study aims to sort out VATs' application purpose and context in the business community and examine the degree to which VATs are incorporated in business learning. For this purpose, we identify the following research questions:

(1) What is the definition concerning VATs, and how VATs' application in the business community is related to the taxonomy of business analytics?
(2) What is the current status of VATs' application at university level?
(3) What arises as additional considerations of VATs in the business community and in business learning?

3.2. Developing Search Strategy and Selection Criteria. An interdisciplinary group of three academic researchers in China's university work for this review to increase reliability. They are associate professors specialized in business operational research, one assistant professor with experienced in educational technology, and one lecturer with focus on applied psychology and information technology. Before full-text review, the research group discusses the selection criteria to achieve reliability consistency. After each review, member check is conducted to improve validity. We contribute a set of skills to analyze the study from different dimensions.

We examined the following four repositories that include important journals and conferences in the context of visualization science and business studies: Web of Science, Taylor & Francis database, EBSCO, and IEEE Digital Library. These four databases are most relevant and scientific for business analytics and important source for visualization science. Meanwhile, given that the VAT is initially proposed by Thomas and Cooks [18], to achieve a comprehensive understanding of VAT tools, the study identified the time frame of articles published in English from 2006 to 2020. Based on these database venues, the search strings follow Carroll's [19] format: (A and B), (A and C and D), and (C and E and F). For instance, title terms and keywords included the following: "visual analytics" OR "information visualization" OR "scientific visualization" OR "interactive data visualization"; AND "business" OR "management" OR "education ∗ " OR "finance," "accounting," "health care," "decision making" OR "business education" OR "business learning." Besides, the relevant disciplinary areas were identified and unique indexing terms for each database were also assured. Search results from each database were imported to a reference management system, and duplicate articles were removed. We create inclusion and exclusion criteria shown below to improve the overall validity.

Inclusion Criteria. Selected articles were included due to the following: (a). peer-reviewed; (b). empirical; (c). related to interactive visualization; (d). focused on business needs and business analytics; (e). concerned with decision-making and business learning.

Exclusion Criteria. To confirm a focus on the current landscape, we excluded articles on the following: (a). visualization is only used for presenting study results; (b). interactive visualization is used as a tool for comparing with static visualization; (c). paper concerns on computing algorithm, software engineering, or unrelated business preference fields; (d). only article abstract without full text.

3.3. Selection Workflow of Our Studies. The research started on January 17, 2019, and ended on February 17, 2020. Initially, our selected databases yield 304 articles and additional 37 articles from references of previous selected articles that are hand-searched. Three authors participated in the screening process. After considering potentially relevant articles based on the title, 116 articles are filtered to the next stage. According to the further review on abstract, unrelated fields are excluded and 77 articles are eligible for VATs in business field and business learning. Then, 68 articles with full text fall into repeated review. We finally identify 58 articles for synthesis after carefully undertaking thematic analysis (Figure 2).

3.4. Data Extraction, Critical Appraisal, and Synthesis. Data extraction involves qualitative thematic analysis [20]. For each article, three authors independently conducted iterative processes of reading text, assigning codes to generate similarities and group differences, conducting meta-coding to examine relationship among a prior theme, and eliciting categories after discussion and reaching a consensus to resolve discrepancies.

We critically analyze the selected articles in three difference stages. First, we identify what definition is regarding to VATs, and what is main application purpose in line with business analytics (RQ1). Second, we examine to what extent the benefit of VATs in business is applied in VAT-enhanced business learning (RQ2). Third, we explore what is the additional information concerning the intersection of VA in business support and in business learning arising from the current review (RQ3). In practice, we initially analyze the variation of VATs in the business community and learn in

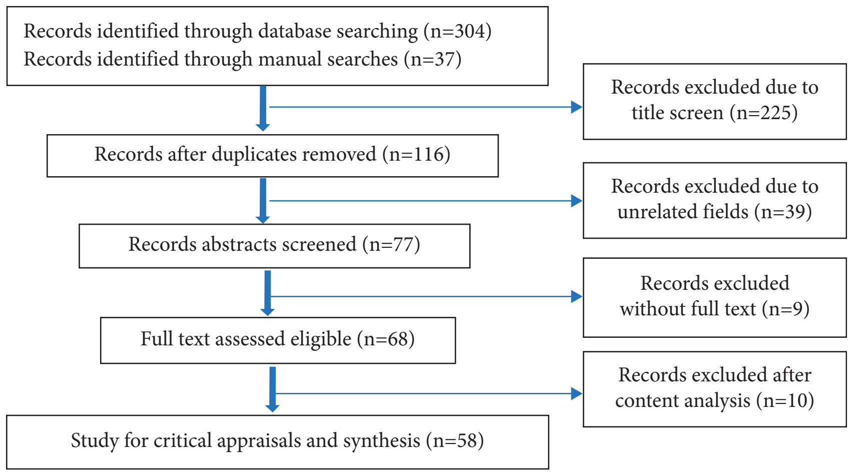

Figure 2: Stages of selection workflow.

accordance with previous literature review and sort out the definitions shared among the studies. Next, researchers mark down the type of study conducted (e.g., qualitative, quantitative, case study, and experimental study), the sample size, the instruments (e.g., interview, observations, and survey), and contextual factors to make a comprehensive overview. To guarantee the content consistent to the study purpose, our research team thoroughly read the full text and ruled out articles. For example, some articles concerning VATs in business context are still deleted because they mainly focus on forecasting future chance and opportunities [21], applying VATs to fasten data mining in business [22] and providing understanding for customer in museum [23].

Based on the business analytic taxonomy (Figure 1), 6 categories of business dimensions were identified. Different groupings of them were discussed to list under the respective taxonomy. Articles concerning on VATs' application in learning were grouped together and classified based on their learning assessment for further comparison with VATs in the business community. The synthesis of findings is provided to guide practical support in business learning with VATs and to identify underexplored areas of research.

4. Results

The studies examined to synthesize conclusion were 58 studies. The 50 out of final 58 studies were reviewed to identify how VATs are utilized in the business community, and the other 8 articles were examined to what extent VATs are applied in higher education.

4.1. RQ1: What Is the Definition Concerning VATs, and How Its Application in Business Community Related to the Taxonomy of Business Analytics? Table 1 shows the output of our analysis of 50 articles. It indicates that VAT facilitates business analysis through reporting the data (descriptive analysis), creating predictive models to foresee future problems and opportunities (predictive analysis), and analyzing to optimize business processes to improve organizational performance (prescriptive analysis) [72]. Following the priori themes (i.e., descriptive, predictive, and prescriptive analysis), 6 categories were derived from articles' coding scheme. The categories were then used in the rest of the study. They are *decision support; marketing analysis; organizational structural operations; business ecosystem prediction; optimized decisions; and* competitive *risk prevention.* Among these 50 articles, three existing VATs were identified in the studies: (1). visual analytics: 35 articles; (2). information analytics: 11 articles; and (3). interactive data visualization: 5 articles. As mentioned in section 2, scientific visualization is probably mainly used in computer science, so it is not found in business analytic context in our research. Other three visual analytical approaches are applied for business as big data analytic tools. According to the articles, visual analytics is the most popular name used in the research, followed by information visualization and interactive data visualization.

The six categories derived from the content analysis are presented in line with business analytic taxonomy.

Decision Support: studies were grouped with sharing the aims of applying VAT tools to present big data information, such that decision-makers can follow the information to evaluate policy or management outcome. In these studies, VATs take the role of providing interactive discovery and showing up complex data information. The focus of application remains on the early phase of decision and performs a visual representation upon the big data [24]. For example, VAT was used to detect the performance of Green Cabs and Uber in New York. It provides meaningful facts for actionable insights [28]. Another study in South African business showed the high value of VATs in day-to-day operations [26]. Besides, these decision support function deriving from VATs also emerges in the areas of online product review [37], changes in consumer behavior [27, 29, 30], supply chain network [8, 25, 32], health enhancement [33, 35], pipeline maintenance [34], and retailing management [31]. The tracking performance is the example of descriptive analytics [73], and understanding this fundamental function of

Table 1: Visual analytical science in business application.

Business analytic taxonomy	Application purpose (context)	Visual analytic technologies (VATs)			
		Visual analytics	Information visualization	Scientific visualization	Interactive data visualization
Descriptive analytics	Decision support	Basole et al. [24]; Basole et al. [8, 25]; Behardien & Hart [26]; Hennig et al. [27]; Poulsen et al. [28]; Wen et al. [29]; yao et al. [30]	AI-Kassab et al. [31]; Basole et al. [32]; Jinpon et al. [33]; Medeiros et al. [34] Forsman et al. [35]; Khan & Hussain [36]; Kim, J. & Kim, D. [37]	Blank	Blank
	Marketing analysis	Ratwani, et al. [38] Wang et al. [39]; Chui et al. [40]; Lozano & del Pilar Villamil [41]; Nankani et al. [42]; Dayal et al. [43]; Ertek et al. [44]; Simpao et al. [45]	Blank	Blank	Ko & Chang [46]; Saidinejad et al. [47]; Franco et al. [48];
Predictive analytics	Organizational structure operations	Jugel et al. [49]; Teng et al. [50]; Buchanan et al. [12]; Noyes & Deligiannidis [51]	Blank	Blank	Blank
	Business ecosystem prediction	Basole et al. [52]; Basole et al. [53]; Park et al. [54]	Basole [55]; Basole et al. [56]	Blank	Basole et al. [57]
	Optimized decisions	Rudolph [58]; Sarlin [59]; Basole & Bellamy [60, 61]; flood et al. [62]; Adagha et al. [63]; Savikhin [64]; Angelini & Santucci [65]; Graham Gal, Singh & best [66]	O'Halloran et al. [67]; Medeiros et al. [68]	Blank	Blank
Prescriptive analytics	Risk prevention	Basole [69]; Pépin et al. [70]; Elias et al. [71]	Blank	Blank	Sarlin [59];

VATs is the most common goal of VATs' application in the business community.

Marketing Analysis: similar to decision support dimension, marketing analysis is another area that frequently applies VATs for descriptive presentation. The category is listed different from *decision support* because our researchers recognize that studies use VATs as marketing segmentation tool rather than only data presentation (i.e., performance dashboard). For instance, enterprise institutes use VATs to take into account market factors such as student fee incomes, budget allocations, environment factors, and others, resembling corporate governance. They make use of VATs for academic collaboration analysis from a real-time dataset in order to extend marketing strategy support for executive teams [42]. Such collaborative business intelligence is also applied in Dayal et al.'s [43] study, resulting in facilitating strategic management [44, 48]. Moreover, the customer analysis is found most in healthcare industry (i.e., electronic health record, [39, 45]; safety event reports, [38]; and public health for disease monitoring, [40, 41, 46, 47]). Indeed, these reports or records facilitate data exploration and trend analysis, specifically in the big data era.

Organizational Structural Operations: organziational sustainable competitiveness in the industry influences venture's survival, growth, and profitability. Different strategic tracks in the industry can ease or confound organizational sustainable development, and entrepreneurs require technology to understand the construction of emerging industry. For example, to enter into a new growing business, VATs' application can help in multilevel structural analysis such as industrial analysis, strategic planning, and entrepreneurial opportunity identification [51]. Also, we found VATs relevant and important for enterprise structural analysis (i.e., enterprise architecture management in [49]; task flow management in [50]; and human resources capability [12]).

Business Ecosystem Prediction: business ecosystems are featured by large, complex, and global networks of organizations, often from diverse market segments to generate and deliver business values [57]. Based on global dynamic markets, the enterprise has to face complex tasks or intra- and cross-organizational relations to react to market influences. There appears a research stream of business ecosystems in this study. They are Basole and his research team (2009; 2011; 2012; 2013; 2015b) and Park and his associates (2016). Researchers propose and develop VAT's application in business ecosystems. They synthesize complex ecosystem, strategic dynamics, and industrial life cycle in the longitudinal dataset to confirm the value of convergence on ecosystem and indicate new business opportunities that are not possible by using traditional tools.

Optimized Decision: visuals can be useful for overcoming cognitive limitations; more importantly, geographical or network displays in VATs show up inherent connections and proportional relationships upon analyst's request. This engages analyst participating in interactive information feedback to forecast and overview macroprudential data for optimized decision rather than merely descriptive decision (compared to previous decision support). We found that VAT was used to increase analyst's comprehension of data stream in risk assessment [59–62, 65, 67, 68], financial modeling [63, 64, 66], and to support profit-maximizing decisions in the value auction framework that are mainly used in the fields of real estate and commercial construction [58]. Illustrating predictive relationship through VAT application demonstrates how VATs assist in reasonable optimal decision.

Risk Prevention: the greatest contribution of VATs is to explore the expected and discover the unexpected [36]. Similarly, identifying hidden patterns and trends behind the data of volume, velocity, and variety, VATs help managers better understand trends and customer opinions [70], and it is also developed for managing global value chain risks, mapping competitive networks, and identifying venture capital flow with expert evaluation [69]. Studies in this category scrutinize VATs as a prescriptive tool to help strategy planning based on correlation aspects of strategic component evaluation that involve eliciting best decisions [58].

Above in all, *decision support* and *marketing analysis* are grouped into descriptive analysis (25 studies in total) because VATs used in these studies are used for business on-demanding reporting. The outputs of them are mostly the identification of problem and opportunities. *Organizational structural operation, business ecosystem prediction,* and *optimized decisions* are grouped into predictive analysis (21 studies in total) since VATs assist to discover predictive trends and associations. The output of them represents inherent relationship or forecasting (i.e., future projection). Finally, prescriptive analysis through VATs shows limited number in existing literature (4 studies in total). Output of VATs strategically conveys and delivers action modeling with complex objectives, providing a set of high-value alternative decisions to enhance business performance. Hence, VATs are demonstrated and widely utilized in the business community with different purposes at respective dimensions of business analytics (Figure 3).

Throughout the studies, researchers found that the definitions of these three tools share similar notions in business context from different angles (Table 2), for example, from the angle of data visualization [18, 74], and [75], from the angle of computer science (Endert et la., 2014), human-computer interaction [13, 79, 82], and from the angle of cognitive psychology [80, 83]. Thus, we conclude VAT is an interdisciplinary approach of merging interactive visualizations and data mining algorithms to support cognitive sensemaking discovery in huge volume of data. The features of VATs include visual representation, interactivity, and science of analytical reasoning.

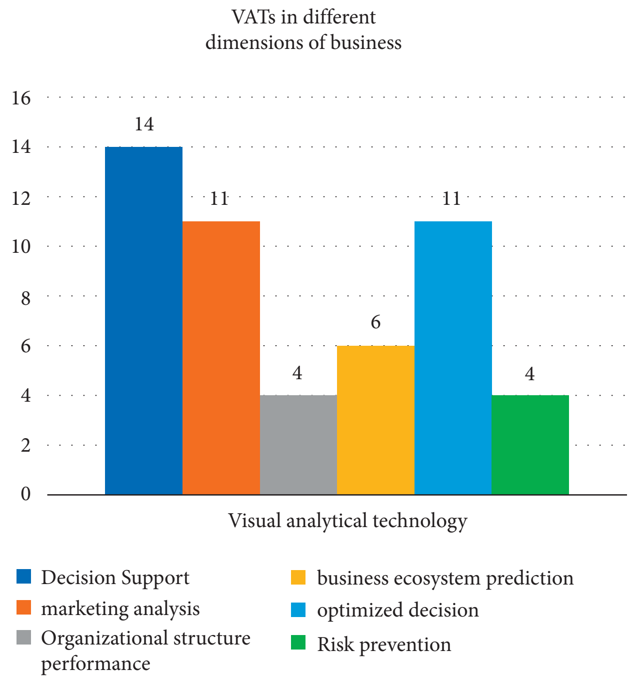

Figure 3: VATs in different dimensions of business.

4.2. RQ2: What Is the Current Status of VATs' Application at University Level? The second issue of this literature review is to identify how the VATs are used in classroom learning. The goal of this step is to explore the existing interaction between VATs in the business community and VATs in business education. This intersection tells how much VATs in the business community are paid attention to educational purpose. Referring to Table 3, only 8 articles show VATs' application in higher education sector that is identified. Four studies are related to business, education and the remaining 4 studies belong to other academic disciplines. With reference to the taxonomy of business analytics, three articles [13, 82, 84] belong to descriptive analytics while only one article is prescriptive analytics [73]. The finding suggests that VATs in business learning are still limited in number. For example, Janvrin et al. [82] compare different types of VATs and provide hands-on opportunity to students by organizing unstructured data for decision-making. Igou and Coe [84] have students apply Tableau (VAT tool) to gain an understanding of data and then use that knowledge to answer business questions concerning a coffee shop case. Another study deals with upper-level business skills and requires students to demonstrate cross-disciplinary competencies (i.e., communication, analytical thinking, and technology) through interactive visualization [13]. Similarly, Kokina et al. [73]'s case helps develop analytic-related and problem-framing skills by mapping business problems with Tableau.

Comparison of studies of VATs in the business community and those in business learning is shown in Figure 4. VATs used as learning tools remain extremely low as compared to VATs in the business community. Furthermore, previous studies mainly emphasize "how to learn and use" data analytic software [89]. They often miss the

Table 2: Definitions of visual analytic approaches used in the studies.

Researcher (s)	Definitions
[18]	Visual analytics is the science of analytical reasoning facilitated by interactive visual interfaces
[74]	Visual analytics combines automated data analysis techniques with interactive visualizations for an effective understanding, reasoning, and decision-making on the basis of very large and complex datasets.
[75]	Visual analytics is an emerging research discipline aiming at making the best possible use of huge information loads in a wide variety of applications by appropriately combining the strengths of intelligent automatic data analysis with the visual perception and analysis capabilities of the human user.
[76]	These kinds of visualizations are specifically designed to support the interactive dynamics required for users' analytic involvement with the data in real time.
[77]	Visual analytics is defined as new enabling and accessible analytic reasoning interactions supported by the combination of automated and visual analysis.
[78]	Visual analytics combines automated analysis techniques with interactive visualizations for an effective understanding, reasoning, and decision-making on the basis of very large and complex datasets.
[79]	The visual analytic methodology is based on combining data visualization, data analytics, and human-computer interaction to solve application problems.
[80]	Information visualization, the focus of visual analytics, refers to the interdisciplinary field concerned with the visual representation of complex information in ways that enhance understanding.
[81]	Visual analytics is the science of marrying interactive visualization and analytic algorithms to support exploratory knowledge discovery in large datasets.
[82]	Interactive data visualization (IDV) facilitates decision-making by organizing and visually displaying data in an easy-to-use interface.
[83]	Information visualization refers to the "use of interactive visual representations of abstract, nonphysically based data to amplify cognition."
[13]	Interactive data visualization refers to visual representations enhanced with interaction capabilities that permit individuals to display multiple visual effects, actively control those presentations, and use those presentations to analyze information.

Table 3: Classroom practice with VATs in higher education.

Author (s)	Course application	VATs	Teaching assessment	Analytic taxonomy
Igou & Coe [84]	Authentic scenario (coffee shop)	Visual analytics	Self-efficacy; task performance	Descriptive analysis
Janvrin [82]	Case study in price and product strategy	Interactive data visualization	Self-efficacy; task performance	Descriptive analysis
Kokina et al. [73]	Problem-based learning (e-commerce of sock's company)	Visual analytics	Self-efficacy; task performance	Predictive analysis
Mirel et al. [85]	Case-based instruction of gene task in biology education	Interactive data visualization	Task completion and task performance; higher-order thinking evaluation	N/A (biology)
Perdana et al. [13]	Authentic scenario on pharmaceutical companies	Interactive data visualization	Technology acceptance	Descriptive analysis
Schweitzer et al. [86]	Course project in computer science	Interactive visualization	Course evaluation on students' reaction	N/A (computer science)
Saraiya et al. [87]	Real-world scenario (gene expression microarrays in life science)	Visual analytics	Task performance; level of insight generation	N/A (life science)
Stenliden et al. [88]	Innovative didactic pedagogy design experiment	Visual analytics	Student's knowledge presentation and written test	N/A (educational science)

coverage of analytic reasoning process or advanced analysis. For instance, the students in above cases are not required to consider questions beyond knowledge visibility, resulting in less transfer skills in insight exploration and prediction. In view of this, little study pays remarkable attention to the VATs enhanced in business learning for predictive and prescriptive analyses. As such, though there has been significant emphasis on improving data analysis techniques for decision-making, very few studies have actually been conducted to investigate the effect of analytic technology in learning outcomes from the learning perspective. That is why Figure 4 shows that articles concerning VAT-enhanced learning are relatively low (line in red) in comparison to those of VATs in the business community. Consequently, based on the low attention of VATs in business learning and insufficient focus on upper-level analysis skill, the research gap in using VATs as predictive analysis tool in learning deserves to be further explored.

4.3. RQ3: What Arise as Additional Considerations of VATs in Business Community and in Business Learning? As VATs

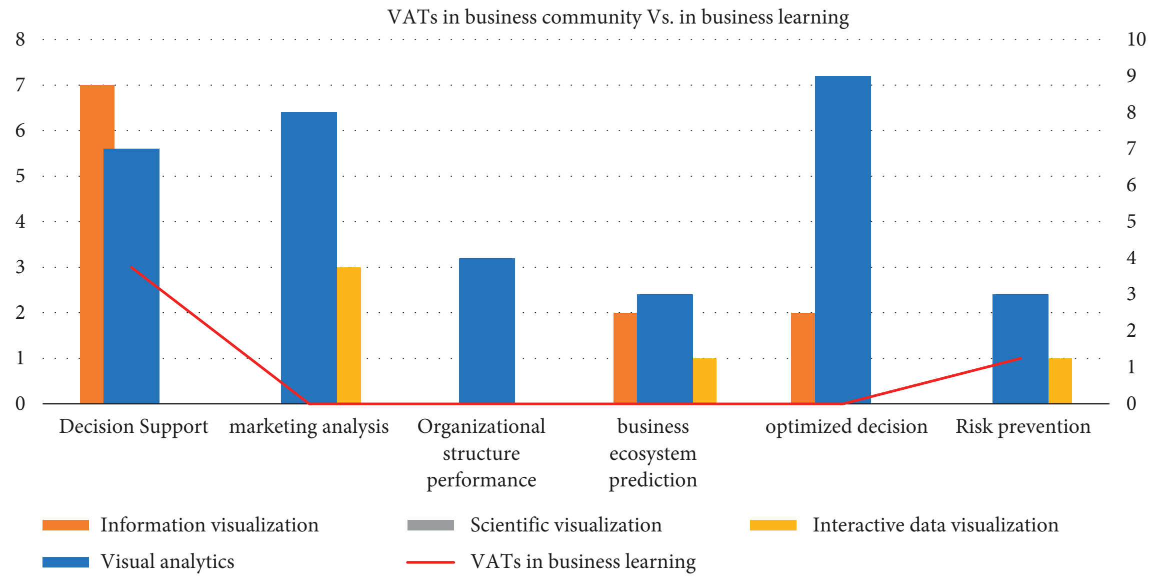

Figure 4: VATs in the business community vs. in business learning.

prevail in business decision-making due to its feature of processing big data, we find that three issues should be considered at the functions of VATs in the business community and business learning. They are (a). presentation formats; (b). context for business learning; and (c). insufficient empirical support on VAT-enhanced prescriptive analysis.

4.3.1. Presentation Formats. Business professionals often use *dashboard* or *storytelling* functions in VATs to support their decision-making process. A dashboard is shown to collect, summarize, and present information from multiple sources so that the user can see at once how various performance indicators are organized [90]. Dashboard has their application in enterprise performance management and decision support (i.e., [45, 61]). In particular, the increasing VAT application in healthcare demonstrates the value of interactive dashboard in highlighting hidden data [38]. In addition, the "tailor" function of storytelling also performs to highlight critical items within very large data resources. In other words, dashboard is used to present important complex data, whereas storytelling is used to tailor specific demand by highlighting key items [71]. Thus, supplemented with the dashboards, storytelling is a powerful abstraction to present the analysis results, conceptualizing threats, and opportunities for business. In a recent study of Stentiden et al. [88], researchers utilized visual storytelling format to incorporate visual analytics (VA) with knowledge visualization (KV) to support student's knowledge construction. Result shows that teachers' storytelling in VA helps students easily create their knowledge by extracting from visual components and comments in dashboard. The above article summarizes that there is a need to enhance VATs with *storytelling* support, where business analysts work over very large data and professionally explain indicators why they consider importance and connections on the dashboard.

4.3.2. Context of Business Learning. Our researchers recognize that the VAT-enhanced learning environment is all configured to describe the real-world case study. With authentic case, the empirical data show that the learning effectiveness such as task performance [72, 81, 83, 87], analytical reasoning, and higher order thinking [13, 84, 86, 87] are in consistent with three level of business analytic taxonomy, respectively. In these reviewed articles, analysis with authentic cases is found to yield better learning outcomes. Students were involved with authenticity of learning materials (i.e., different real-world business cases) to share practical solutions with VATs. Authentic problem task with VAT-enhanced business learning prepares students to become competent problem-solvers and fosters higher-order thinking.

4.3.3. Insufficient Empirical Support on VAT-Enhanced Prescriptive Analysis. Several studies [58–60] indicate that modeling prescriptive analytics goes with advanced analytical reasoning skills including domain knowledge, cross-disciplinary knowledge, and complicated cognitive activities to yield reasonable solutions. VATs, as cognitive amplifiers, assist decision-makers to find evidence indicating a possible shift from value exploration to value capturing. It means that when descriptive business analysis switches to predictive and prescriptive analyses, value is added to the enterprise for strategic operations. However, we only found a small number of articles that VATs exert as prescriptive tool in both the business community and business learning. Thus, empirical research data are urgently needed to support how VATs function under prescriptive analytical reasoning.

5. Discussion

Having reviewed the relevant literature on VATs' application in the business community and in university learning, it suggests that VATs in the business community mainly focus on visual analytics, followed by interactive data visualization (IDA) and information visualization (InfoVis). Owing to the big overlap between InfoVis, VA [91], and IDA [13], related articles share the definition of visual analytics as "the science of analytical reasoning facilitated by interactive visual interfaces" [18]. Specified on three prior themes of business analytics, we classified VATs' application purpose into six dimensions. As data analytic tools, VATs take effect in *decision support; marketing analysis; organizational structural operation; business ecosystem prediction; optimized decisions; and* competitive *risk prevention*, basically from descriptive analytics to complicated prescriptive analytics. VATs stay more in the descriptive level ($n = 25$) and predictive level ($n = 21$) than prescriptive level ($n = 5$), which contradicts the optimized function of VATs (i.e., storytelling with dashboard). Generally speaking, the emerging research field of VATs has the advantage to combine big data analytic manipulation and knowledge representation supported with human cognitive strength to predict future patterns. The storytelling of holistic view positively related to prescriptive decision-making [91]. Thus, advanced level of prescriptive analytics should be considered in the future business community for precise strategic planning.

In addition, the selected articles indicate a high proportion of VATs' application in descriptive and predictive analyses. This interest may increase the attractiveness of applying VATs in business learning. However, there is still a lack of empirical data about the benefits of VATs in higher education ($n = 8$) and even less in business learning ($n = 4$). The poor figure shows that even VAT is important and is recorded to alleviate human cognition overload, and it is not prevalently used in educational scenario. The findings are in accordance with Mikalef et al.'s [3] review. In their review, although many companies build up big data analytic infrastructure, massive decisions do not rely on the information extracted from data analysis but on managerial experience or individual intuition because of shortage in business analytic skill and knowledge. This urges the formation of data-driven culture, which is highly dependent on upper-level data analytic competent. Unfortunately, no or limited attention is paid to the talent cultivation upon this issue. Little application in business learning leaves the critical issue concerning VATs' function of analytical reasoning essentially unobserved.

Furthermore, the results from our systematic review illustrate that while VATs have been utilized in the business community, the benefits of VATs have not been received attention in business education. The unbalanced practice exists between the industry and the university. In industry, VATs help to gain a comprehensive understanding of what happened in the past, what is likely to appear in the near future, and what a decision-maker should consider in the future operation. It is a growing belief that tomorrow's enterprise will not compete solely based on past performance, but they will enhance their competitive posture with the way they transform their data to predict actionable knowledge via advanced analytics [15]. On the other hand, VATs as analytical reasoning tool do not exert most in prescriptive analytical level in classroom learning. What used in classroom learning in most practice only remains on descriptive-level analysis rather than predictive and prescriptive analyses. There remains a gap in how predictive and prescriptive analyses are fostered in business learning to enhance task performance and self-efficacy. Therefore, presentation format (i.e., storytelling or dashboard) and authentic business environment provide implication for educators to combine educational theory with VAT-enhanced learning.

6. Implications and Research Agenda

Policy-makers in the business community increasingly use VATs to see emerging big data and explore insights from the output to predict business opportunities. Based on the systematic literature review, we found that VATs are widely applied in business practice across six dimensions at three business analytic levels. There is a tendency that VATs receive more and more attention. However, the application in the business community remains in descriptive and predictive analytic levels. Prescriptive analytics of VATs is still lack of enough studies for its potentials and contributions to business world. More investigations should be developed to optimize the benefits of VATs. On the other hand, to keep pace with industry, business learning should be acquiring these same methods to gain insight with advanced technology. Maximizing the functions as cognitive amplifiers is to examine the learning effectiveness of analytical reasoning in business learning, which is equivalent of prescriptive analytical level. Accordingly, we propose a future research direction for the development of VAT-enhanced business classroom.

First, bringing VAT-enhanced business cases in RQ1 into the classroom may enable instructors and students to better understand the purpose and benefits of VATs in business industry. Ensuring college students can work with big data is important in today's environment due to its prevalence in the business community. This review takes an active step in fostering collaboration for academia and industry to prepare students for careers. As Wymbs [7] suggested to use real-world practice to align business course with need of practices, instructors can directly apply articles (in RQ1 section) that spread across six dimensions of business context as authentic learning cases. So future studies can explore the effect of authentic VAT-supported case in the business community on learning the effectiveness of business strategic analysis.

Second, VAT offers the advantage of alleviating cognitive load on visualization. It should be considered as cognitive amplifier when introduced to business learning, which helps to promote students' metacognitive development and knowledge transfer. VATs engage students in higher-order reasoning environment [85], such higher-order reasoning includes drawing meaning from patterns, breaking problems into parts, rationally arguing, demonstrating the quality or importance of information, and weighing the relative value of evidences [92], resulting in improved learning outcomes [13]. Studies on how VATs act as cognitive tool in fostering critical thinking in business learning needs to be further investigated. It suggests to apply educational theory (i.e., constructivism, cognitivism, or social cognitive theory) to test the effect of VAT-enhanced learning on student's learning strategy.

Finally, completing task with advanced business analysis demonstrates students' cross-disciplinary business competencies, such as students' upper level of business communication with storytelling in dashboards. Hence, teaching practice should have potential to elicit storytelling in relation to business predictive and prescriptive analysis. Addressing business problem or exploring opportunities in a single view of dashboard can be set as pedagogical objective to activate higher-order thinking. Further studies might shed light on how VATs provide wisdom to make prescriptive insight to train storytelling in business intelligence [71].

In summary, current business data analytics course still stays in its early stage, with insufficient commonly accepted model and inappropriate pedagogical design [6]. Instead of adding more courses, incorporating VATs is to revise existing courses to include learning objectives that are necessary for a business student to be data competent [4]. We advocate that bringing these VATs into business learning gains benefit for students in aligning up-to-date business analytics to business learning in big data era and in fostering problem-solving ability and higher-order thinking.

7. Conclusions

Historically, domains such as business intelligence would require a single analyst to deal with data and develop a model to answer operational questions [12]. Currently, with the rapid development of data science, organizations are struggling to develop practices for intelligence analysis in big data era. A variety of data analytics techniques faciliates the develoment of VATs. VATs help companies to stay competitive by giving a complete overview of critical information at all times (i.e., dashboards), providing users with logical connections between cause and effect within an enterprise or industry figures so that the issues can be proactively tackled. The field of visual analytics emerges as an opportunity to generate insightful knowledge and inform effective decisions. Nowadays, anything involving customers, a key concept in business, could benefit from VATs. Lack of such strategy-driven big data analytic capabilities results in less competitive performance. This study presents a literature review (a). to identify existing VAT approaches and application purpose in business context and (b). to examine the gap and future opportunities for conducting business analytics in classroom practice that facilitates advancing of these fields. This study, therefore, opens a new promising direction for business classroom practice, with possible implications for enhancing VAT-integrated learning in business course. Further studies should empirically test and evaluate the research agenda using surveys, focus group, observation, in-depth interview, and case studies.

This study makes two contributions. First, the identified VATs' definitions and application context might offer value to practitioners, who are considering implementing VAT-enhanced classroom teaching to cultivate students' data analytical ability. Second, it contributes to provide insights for predictive analysis and upper-level business skill by examining a taxology of business analytics that gives impetus to utilize data analytics in business learning.

The main limitation of this review exists is as follows: (a). the selection of articles may bring bias to the statistical result due to the limited database that we used. However, the database and selected articles are relevant and academic trustworthy venues. (b). The research team did not include an expert in data science that would have benefited from computer science. Nevertheless, the interdisciplinary composition of our team allowed us to capture value articles and synthesize the review. Future concerns can focus on the ongoing development of big data analytics in different business contexts, on what is already known in business learning, and on what will be discovered in the near future.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare that they have no conflicts of interest.

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