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A design-based research approach for developing data-focussed business curricula

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Abstract

Although existing data science educational programmes develop talent and produce graduates, business-focused data science curricula comprising essential skills oriented to business and managerial data with associated analysis, remain underserved. Current pedagogy has focused either on data science or on purely analytic technical aspects. There is therefore, an opportunity to rethink how institutions can develop innovative data-focussed education programmes, addressing both modern industry and community demands. As both academia and industry strive to integrate applied learning, transferable and enterprise skills into business and sciences, this paper proposes a design based research approach (DBR) for designing such a new interdisciplinary data science teaching curriculum as a foundation to deliver business undergraduate degrees in Business Data Science. Adopting a design science method our proposed DBR illustrates effective utilities for conceptualising and evaluating a fully functional new degree programme - Bachelor of Business Data Science. Ten senior business information systems academics and five analytics industry practitioners in Victoria, Australia were interviewed in three iterative prototyping phases followed by a final focus group session with business information systems students that evaluated the proposed structure. The findings suggest that proposed DBR ensures the design of an innovative data science degree that may meet growing industry and interdisciplinary demands. The paper concludes by discussing overall feasibility of the proposal in the Australian higher education sector, particularly for the case context of an Australian University.

Keywords Business curriculum · Information systems education · Data science education · Higher education

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1 Introduction

The paper promotes curriculum design through an innovative design-based research (DBR) methodology – informed by the established research trend in information systems of design science research (Simon 1996; Hevner et al. 2004; Gregor and Hevner 2013) – in the development of a new teaching programme. In this paper we introduce and explain the approach, illustrating in the context of our case at a medium sized metropolitan university in Australia.

Recognising that businesses are increasingly dependent on data-driven strategies for growth and productivity, higher education providers should offer academic programmes for the development of graduates that help address this dependency. According to IBM, by 2020, the world will be creating more than 35 Zetabytes ($3.5\ X\ 10^{22}$ bytes) of data every year (Pearson 2018). These huge and diversified data sets can be useful for providing answers and solutions to some of the biggest business and community problems. Current curricula have focused mainly either on data science or on pure analytic and technical content aimed at enhancing approaches and skills for data exploration and processing. However, the focus on technology and statistics tends to overlook development in business-focused data science in which graduates with business data oriented skills and understanding may meet the growing demand for data-oriented analytical thinking.

Modern businesses and industries now regularly practice data-driven decision making (Herodotou et al. 2017), however, the information systems (IS) discipline in higher education remains largely limited to producing business analysts or IT support service professionals, most of whom are then trained as graduates in-house for a specific-domain or business technology. A growing number of students are completing undergraduate degrees in business IS and entering the workforce as analysts with limited capabilities in developing and maintaining IS solutions for the demands of managerial decision making. Data science topics have not traditionally been a major component in their business degree programmes although it is a rapidly developing area in engineering and science education. Current IS teaching falls short of incorporating or promoting data-oriented knowledge to produce more effective IS graduates (e.g. data analysts, business data experts and translators) with transferable skills (Asamoash et al. 2017). Likewise, current data science based courses offer well-structured approaches for the utilization of computational and statistical methods, but are more aligned to science and engineering careers, often assuming a certain mathematical background. Although academic 'data science' programmes are data oriented, curricula and pedagogy typically reflect discipline-specific perspectives and may be further narrowed toward the computational and statistics curriculum that are the primary domain of academic discipline (Asamoah et al. 2017; Hardin et al. 2015a, b; Asamoah et al. 2018). The need for tailoring such knowledge and skills to meet wider business demands is largely ignored, for example, eschewing foundational skills in business data capturing, processing, analysing and presenting aimed the application of data for decision making and business process understanding.

Despite the narrow foci suggested above, interdisciplinarity is not a novel concept in higher education, indeed it is often espoused as a function or aim of modern education (Ivanitskaya et al. 2002). An interdisciplinary data science education in which both business and relevant technological skills are combined provides, "*a practical* *perspective where data scientists are seen as business analysts"* (Asamoah et al. 2017; p. 1). Lake (1994) defined the benefits of offering interdisciplinary programmes for students as moving beyond simpler forms of knowledge acquisition to a deeper assimilation of cross-disciplinary applied concepts. The students in an interdisciplinary programme may better achieve critical thinking or problem solving skills in cross-functional analysis, connecting internal and external elements in a particular domain. Albeit piecemeal, interdisciplinary education in data science is emerging both in business schools and commercial online training (such as *DataCamp* and *Udemia*) around data exploration, data manipulation and data representation, attempting to address the continuously evolving requirements of data-driven business contexts.

There is an opportunity to rethink how higher education providers can develop innovative data-focussed education programmes catering for the complex demands of modern industry and business communities. We therefore propose an interdisciplinary platform as a foundation for delivering relevant, business focussed, data science education.

As both academia and industry strive to integrate applied learning and transferable skills into business and sciences, this study introduces an approach for developing a new interdisciplinary data science curriculum as a foundation for undergraduate degrees in business data science. Design Science Research (DSR) methods have gained increasing attention in information systems research (Hevner et al. 2004). According to the Design-Based Research Collective (2003), its educational technology variant, Design Based Research (DBR[1]) enables developing, enacting and sustaining innovative learning approaches. Recent studies in educational research (e.g. van den Akker et al. 2018) also promoted DBR when designing and evaluating major new programmes. Following Carstensen and Bernhard's (2019) assertions that DBS can significantly enhance our understanding of learning in technical subjects such as engineering, we suggest that DSR knowledge may be used to complement DBR in the conceptualisation of a new degree programme in data science; as Carstensen and Bernhard (2019, p.89) note, *"Such work aims to improve educational practice and develop educational theory at the same time ... design science complements and extends the DE/DBR approaches in educational research by providing tools that can be used to describe and analyse the content of the design process and the design cycle"*. We describe and explain our proposed DBR method within the context of a medium sized, modern, Australian university, following an iterative design process involving students, senior academics and relevant industry professionals. The proposed DBR approach comprises three separate phases: phase 1 is concerned with identifying the needs of the proposed degree programme; phase 2 concerns designing and developing artefacts into degree programme structures; and, phase 3 is a feasibility analysis for evaluating the developed degree structures.

Good design research, *"must lead to sharable theories that help communicate relevant implications to practitioners and other educational designers"* (DBRC, 2003, p.5) and is also an explicit requirement of DSR methodologies. The approach

[1] DBR helps create and extend knowledge focusing on *"designing and exploring the whole range of designed innovations: artefacts as well as less concrete such as activity structures, institutions, scaffolds, and curricula"* (Design-Based Research Collective 2003, 5–6) (Design-Based Research: An Emerging Paradigm for Educational Inquiry, Educational Researcher, Vol. 32, No. 1, pp. 5–8p.5) http://www.designbasedresearch.org/reppubs/DBRC2003.pdf

reported here adopted Gregor and Hevner's (2013) communication schema by focusing respectively on: problems; contributions towards a (new) solution; and, application of that solution. Our primary contributions to curriculum and pedagogical knowledge concern a better understanding in improving programme offerings, ways of learning and relevant thinking, in the design of interdisciplinary data science offerings as feasible outcomes. We aim to address these through introducing a new DSR based methodology for developing a degree programme, considered here as a design artefact.[2] DSR has been practiced increasingly in last two decades in the IS disciplines both for developing solution frameworks and in providing conceptual and fundamental knowledge for addressing theoretical gaps. DSR methodology offers support for: 1) developing new solution artefacts for known problems; 2) developing new solution artefacts for new problems; 3) applying known solution artefacts for known problems; and, 4) extending known solutions to new problems. In this design study, we focus on extending an existing artefact (a degree programme) in addressing new issues of incorporating data science education into the business domain and creating a variety of cross-functional topic areas in the curriculum and delivery of the learning and teaching programme.

The next section provides some contextual background while section 3 presents a detailed methodological description. Sections 4 and 5 provide the findings of the study, while section 6 details the evaluation of the proposed curriculum. The last sections provide a discussion and conclusion in which further research directions are considered.

2 Background

2.1 Data science education and its demand

Hayashi (1998) defined data science in a broad sense, as a new, *"... concept to unify statistics, data analysis, and their related methods, but also (comprising its) results"*, thus encompassing all activities for analysing and understanding phenomena through data. It employs techniques and theories drawn from many fields of science such as mathematics, statistics, information science, and computer science. Data science was described as a 'rebranded statistics discipline' by Cleveland (2001), and most now view data science as an interdisciplinary field that uses *"scientific methods, processes, algorithms and systems to extract knowledge and insights"* (Dhar 2013). As an educational programme it often includes managing various forms of structured and unstructured data.

Higher education providers have experienced a growing number of students in statistics and mathematics seeking to become data scientists, data experts and data engineers; positions that require skills related to, *"understanding how to use databases and other data warehouses, scrape data from Internet sources, programme solutions to complex problems in multiple languages, and think algorithmically as well as statistically"* (Hardin et al. 2015a, b, p.343). These data science topics have not traditionally been a major component of undergraduate programmes in statistics or information

[2] An artefact is always made with a purpose, it can be a construct, model, framework, solution instantiation, or theory that serve defined or particular purpose (Gregor and Hevner 2013; Vaishnavi and Kuechler 2008).

systems. Consequently, there is an opportunity to contemplate curricular changes to address these additional learning outcomes and graduate capabilities.

With, for example, IBM expecting that by 2020, analytics jobs increasing to 2,720,000, Hardin et al. (2015a, b) described the importance of enhancing data science proficiency, with instructors using appropriate examples and resources for data science in their statistics curricula. Also by 2020, Forbes predicts that yearly demand for data scientists and other related roles will reach about 700,000 with a projected 28% increase in demand for professional data scientists (ICS 2018; Columbus 2017). There is huge demand in our Australian context, with the CEO of the major Telco (Telstra Corporation Limited) commenting, *"We cannot find in Australia enough of the skills we need on the scale that we need them, particularly in software engineering or analytics" (source:* https://www.abc.net.au/news/2019-01-30/telstra-boss-calls-for-end-to-unhealthy-immigration-deabte/10764166). Further, Jaafar (2018)[3] suggests that:

> "What employers will be wanting are honed programming and tech skills in all sort of data modelling, predictive modelling and dashboarding, with an ability in the languages R, Hyphen, Python and SQL. Depending on the data scientist, you can use Tableau or more recent big data tools like Hadoop."

These identified areas seem helpful for informing graduate capabilities and potentially increasing their employability in business industries, as data analysts, data scientists, data engineers, and business or data translators. Education related to data analytics has become a new market demand in almost every sector for ramping up digital capabilities of many businesses. Viewing data science as, *"a fusion of artificial intelligence and business knowledge"* (Christian 2018), Australian retail giant Wesfarmers has opened a dedicated data analytics centre, creating employment opportunities anticipative of many future roles and job functions. Wesfarmers[4] interests in digital capabilities includes several new data projects set to increase growth at retail chains including *Bunnings, Kmart, Target and Officeworks.* The employment need is clear, given that data science for business related fields is now perceived as a major driver for organizations that seek a competitive advantage.

Such expected demand indicates a need for training well-qualified business data scientists able to generate insights from large amounts of multi structured data accumulated in businesses. As implied earlier however, a growing number of students are completing undergraduate degrees in statistics and entering the workforce as data analysts but with shortfalls in their education around business technology.

2.2 Interdisciplinary teaching approaches

As described above the concept of interdisciplinarity is not a novel aspect in higher education. Asamoah et al. (2018) proposed an interdisciplinary course structure in data science sharing perspectives and experiences in its development and offering. This

[3] Jaafar, N. (2018). The Rise of the Data Scientist, URL: https://www.launchrecruitment.com.au/news/rise-of-data-scientist/

[4] Christian, R. (2018). Wesfarmers To Open Data Analytics Centre For Retail Growth, URL: https://www.channelnews.com.au/wesfarmers-to-open-data-analytics-centre-for-retail-growth/

course targeted students with developed computing and mathematical backgrounds that matched the typical prerequisites for MIS or CS junior courses. The course developed the skills-sets necessary to ingest, analyse, and make predictions about data in practice and provided the foundation necessary to pursue an advanced data science certificate or a graduate programme. Cassel (2011) argued for interdisciplinarity in computing curricula, proposing the merging of silos in disciplines regardless of the varied goals and motivations of those disciplines. Very few studies advocate this approach, i.e. merging technical disciplines into business disciplines. However, a simple merging of siloed teaching units and sequences of unite doesn't afford an application of design principles such that different degrees of interdisciplinarity can be created to offer dynamic platforms for teaching and learning.

Likewise, business industries have tended to produce 'data focused' decision support experts, most of whom are trained, *"…in-house in a specific domain with technologies from a specific vendor"* (Asamoah et al. 2017, p.01). Such in-house based training would be unlikely to produce an overarching impact in both research and practice, i.e. the discovery of knowledge as well as its application and integration. Moreover, going beyond short-term business needs through generic skills development may better inform the utilization of computer or information sciences and statistical approaches within a specific domain. Current trends to develop data science degree courses attempt to address some business demands, however, most attempts have emphasised narrow perspectives, converging on technological paradigms. A method is needed that will enable a systematic procedure for developing an interdisciplinary platform of data science courses, where faculty members, students and industry experts exchange their knowledge. Such an environment where domain-specific, multi-disciplinary and technical skills are studied to the benefit of students and future employers can be helpful for the development of a data science course. A business data analytics professional can be variously seen as a data translator who understands and interprets value and meaning of data, who can produce actionable insights for improving business strategies and operations, and as an expert in advancing data analytics technologies using data mining, Artificial Intelligence, and Machine Learning algorithms to the discovery of new knowledge that they themselves synthesize and report on (Asamoah et al. 2017; Conway 2010). Business oriented data science education and knowledge is mainly focused business data management for meeting the demands of managerial decision making and equiping business graduates with an understanding of data oriented challenges faced by organisations through concepts, best practices, tools and techniques for data analytics. Thus, it is important to inform course development and evolution using a method that provides a strong foundation for multidisciplinary curriculum design in data science. This study adopted DBR principles in describing the development of such a multidisciplinary curriculum and is detailed in the next section.

2.3 DBR methodologies for developing educational artefact

DBR has become one of the more popular methodologies for the development of sustained innovation in the education sector (Bell 2004). DBR is defined as, *"a systematic but flexible methodology aimed at improving educational practices through iterative analysis, design, development, and implementation, based on collaboration* *among researchers and practitioners in real-world settings, and leading to contextually-sensitive design principles and theories"* (Wang and Hannafin 2005, p. 6). Li and Chu (2018) described this methodology as highly interventionist, assisting the investigation of educational improvement by bringing about new forms of learning. Our aim in this study is to improve offerings to meet the perceived demands of modern-day industries as a contribution to improving interdisciplinary data science programme offerings. Table 1 illustrates some examples of previous DBR approaches.

3 Research methodology

3.1 Design strategies

DSR complements traditional design methods to produce new understandings and generally focuses on constructed realities and delivering solution outcomes as new sources of knowledge. Vaishnavi and Kuechler (2008) argued that DSR allows multi-paradigmatic lenses for researchers to investigate socially constructed realities for developing fundamental knowledge. Carstensen and Bernhard (2019) used DSR to analyse the method used when deriving the, 'learning of a complex concept' model for an engineering course, and supported Vaishnavi and Kuechler (2008), noting that a major strength of DSR is that its underlying theories are based on iterative processes used both in the development and evaluation of artefacts as well as the ongoing refinement of the designed artefact – in the case of this study, a programme structure and informed curriculum.

Table 1 Example of DBR approaches for designing educational artefacts

Studies used DBR methodologies	Descriptions
Norwich and Ylonen (2013)	The study used a DBR approach for developing a new area of teaching focussing on pupils with moderate learning difficulties. The DBR approach was based on five steps: 1) plan lesion study intervention; 2) lesson studies and their evaluation; 3) review, revise first phase lesson studies; 4) plan second phase lesson studies; 5) evaluation and conclusions.
Li and Chu (2018)	The study described a DBR approach for supporting teaching and learning of Chinese writing among children through the development of a wiki-based collaborative process. The DBR methodology is consisted with three phases of design, with research and iterative processes for questions addressed in each research phase.
Wolcott et al. (2019)	The study described a DBR approach for bringing an intervention in pharmacy education by connecting appropriate theory to improve teaching and learning practices. The DBR included three phases: three iterative phases: 1) analysis and exploration; 2) design and construction; and 3) evaluation and reflection.
Koivisto et al. (2018)	The study introduced a new DBR concept and its appropriateness in creating models for educating simulation facilitators. The DBR approach consists of five phases: 1) systematic literature review; 2) analysis of current programme; 3) development of a prototype; 4) testing prototype; and, 5) analysis of the testing and refining the prototype.

DBR has been described as, *"… the educational technology variant of design science research (DSR)"* (de Villiers and Harpur 2013:252). The aim of the research reported in this paper is to describe a DBR method which adopts DSR techniques to study the potential development of new bachelor degrees in business data science and thereafter the evaluation of the conceptualised programme through iterative refinement, capturing senior academic, industry professional and student contemporary demands and requirements for such a programme.

DBR studies have been introduced for various educational design purposes over the past decade. For example, Starcic et al. (2013) described qualitative DBR research to identify the importance of quality user-interface designs used in teaching and learning. Their study described contributions in the design of user-interfaces in computer-assisted learning environments, indicating the value of DBR studies in improving learning and teaching design and provision. In nursing education programmes, Smit and Tremethick (2013) adopted a group discussion method in developing an interdisciplinary course to address the needs of a wide range of students, faculty and other stakeholders in providing new opportunities for nursing students. Our strategy is likewise to closely involve students, faculty members and other stakeholders in developing a new teaching programme, using DSR methods for capturing these multiple perspectives. It is argued that this method is better aligned to the learning experiences of business graduates with technological career paths and that it addresses the concerns of educational researchers, policymakers, and practitioners who criticise educational research as being divorced from the problems and issues of everyday practices (National Research Council 2002). Our aim is to design a sustainable education programme to support technology-enhanced innovation in improving future-focussed business higher education practices.

DSR approaches offer principles and perspectives that complement positivist, interpretive and critical viewpoints for conducting research. Hevner et al. (2004) asserted that DSR approaches assist in two primary activities – in the creation of new knowledge through design of novel or innovative artefacts (things or processes) and in analysis of the use of the artefact and/or performance through reflection and abstraction. Design means, 'to invent and bring into being' and thus deals with creating or improving artefacts, products and processes (Miah 2008). In this instance, our aim is to uncover a new understanding of using DSR for developing interdisciplinary educational programmes.

DSR and a view to the future are already embraced at a very broad level at the authors' own institution which believes that the dynamism and uncertainty of work and life in the future is an exciting opportunity that can be anticipated and designed for. Described as student experiences and outcomes that prepare them for their futures, these intended outcomes rest on three pillars – *'tech ready'*, *'work ready'* and *'life ready'*. Tech ready because advanced technologies, such as artificial intelligence, automation and big data, will become as ubiquitous as the internet is today. All students, no matter what they are studying – whether science, technology, education, nursing, business, arts or any other course – will need to understand and become proficient in the application of these technologies. These technologies are therefore incorporated into all degrees, meaning students graduate ready to work with the technologies that are transforming the world. Work ready is to develop the portable skills and dispositions that can enable graduates to navigate the non-linear work trajectories of the future. These include developing the entrepreneurial, creative and critical mindsets that employers value but that also enable the creation of opportunities, products, projects that we value as communities in our locality and beyond. Life ready sees the processes of globalisation as opportunity to create greater networks of influence and change, to become global citizens; adaptable, resilient people with deep concern for social justice today, and with an eye to the future.

3.2 Interdisciplinary methods

Interdisciplinarity implies crossing traditional discipline boundaries by conjoining more than one discipline to create a single independent learning and teaching platform (Klein 1990) and thereby, to address any contemporary education needs. Developing a combined platform must inherently acknowledge the established topic while going beyond the barriers of siloed cultures of specialization. For instance, it is important to combine prominent concepts and cross-functional knowledge from physics, chemistry, and mechanical and electrical engineering for designing course in nanotechnology (Porter and Youtie 2009). Traditional methodologies of course development for interdisciplinary education involve faculty members collaborating in the merger of subject areas and teaching materials, producing a new course that has never been offered before. However, faculty members or administrators may lack contemporary industry knowledge, community demands or student views of future trends in learning and employability. To design a modernised course in a truly interdisciplinary manner (that may better inspire students to see how the real business world may be functioning in future), it is important to adopt a broader methodology and set of inputs.

Way and Whidden (2014) classified interdisciplinary methods as broadly, either tightly-coupled or loosely-coupled. Tightly-coupled approaches are focused on intensive parallel tasks among faculty and administration members with highly dependent topics that are integrated through team effort. Conversely, a loosely coupled approach is flexible and can overcome many of the organizational and administrative challenges with traditional or more tightly-coupled approaches, while at the same time offering an appropriate environment that considers both faculty members and students with much of the same cross-disciplinary benefits. This approach decouples much of the dependencies between the topic areas being taught, which would be an important element of demand-driven teaching and learning, such as in business schools or under the broader 'unbundling' contemporary agenda in higher education. The loosely coupled approach[5] thus complements DSR methods for developing our proposed new course structure.

The relationship to design research in education has been described by Owen (1997) with reference to developing a conceptual discipline map comprising two axes: Symbolic/Real and Analytic/Synthetic (Fig. 1). According to Owen (1997):

> "The horizontal axis of the map positions disciplines according to their defining activities: disciplines on the left side of the map are more concerned with exploration and discovery. Disciplines on the right side of the map are

[5] Way and Whidden (2014) defined the loosely coupled approach for developing a new interdisciplinary course for computer science that brings together student needs and faculty preferences in order to maximizing the chances for successful and demand oriented learning. The approach creates multiple merging points so that faculty members can effect an interdisciplinary learning experience.

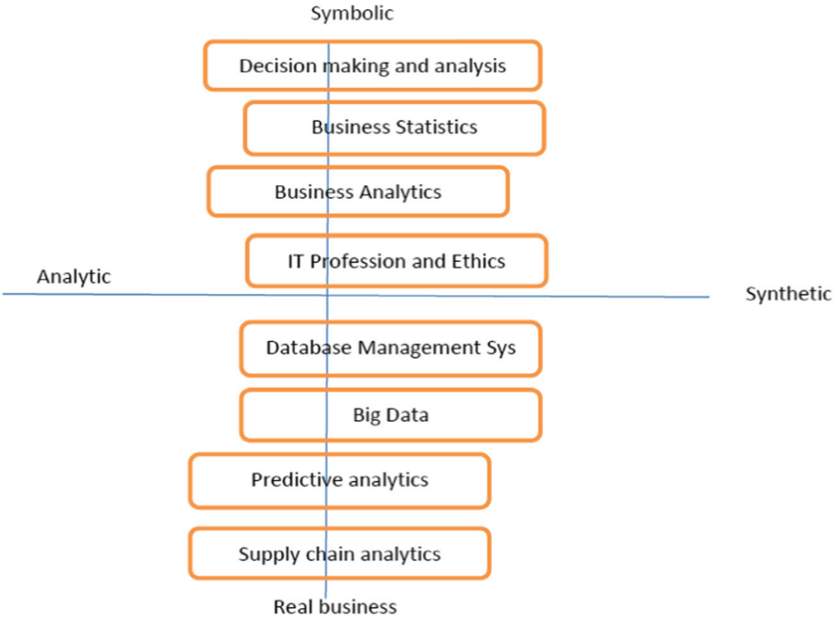

Fig. 1 Conceptual axes analysis adopted from Owen (1997)

> characterized more by invention and making. The vertical division, the symbolic/real axis, characterizes the nature of the subjects of interest to the disciplines—the nature of the phenomena that concerns the research community. Both axes are continua and no discipline is exclusively concerned with synthesis to the exclusion of analytic activities."

Following this example, we initially develop the map of our programme as illustrated in Fig. 1 below.

Bachelor degrees in data science are still relatively new and emerging within the Australian higher education sector. Only a few of the metropolitan universities have offered this type of bachelor degree programme, with the offerings mainly focused on an engineering science disciplines such as statistical and computational principles for managing large-scale data. The career goals are primarily science and engineering oriented, which may not meet the demands of business and operational perspectives. For example, the University of Western Sydney[6] has recently offered a course structure that comprises subjects focused on data analytics (e.g. thinking about data; analytics programming, intro to data science, predictive modelling, visual analytics, social web analytics, allocation of big data and discovery projects), while the University of Melbourne[7] has offered a course with a statistical and computational career orientation, comprising subjects: Calculus, Foundation of Computing, Linear Algebra, Foundation of Algorithms, Probability, Elements of Data Processing, Statistics, Machine Learning and Applied Data Sciences. The University of New South Wales[8] has also recently

[6] URL: http://handbook.westernsydney.edu.au/hbook/course.aspx?course=3734.1
[7] URL: https://study.unimelb.edu.au/find/courses/major/data-science/what-will-i-study/
[8] URL: https://www.maths.unsw.edu.au/futurestudents/data-science-and-decisions

offered a similar bachelor degree, the "Bachelor of Data Science and Decisions" that features mathematics, statistics, computational and data science oriented subjects. These higher education degree programs develop skills and capability in engineering and science oriented disciplinary fields and perhaps overlook valuable learning and teaching opportunities in business data-driven knowledge and other applied education development areas. To explore perceived demand for programmes that may include these latter opportunities, the authors research canvassed opinion using a modified DBR methodology described in the next section.

3.3 Methodology

Simon's (1996) influential paper differentiated artificial sciences from natural sciences, following Nunamaker et al. (1991) who produced a seminal paper to describe the value of DSR for conceptual design and development, describing the designed artefact as, *"… development of new ideas and concepts, and construction of conceptual frameworks, new methods, or models"* (pp.94). As mentioned earlier, DSR provides supports both for innovative conceptual artefact design and relevant new knowledge creation (Gregor and Hevner 2013). de Villiers and Harpur (2013) suggested that DSR and DBR are not merely development models but both have independent roots in Simon's design science and emphasize the research processes involved in the design and development of products and environments, particularly in complex domains such as education. Several other DBR studies also supported this argument (c.f. Carstensen and Bernhard 2019).

Several DSR methodologies have been introduced for design studies in which design and evaluation are the two vital tasks. For example, Hevner et al. (2004) offered seven design guiding principles; Vaishnavi and Kuechler (2008) provided six design steps; and, Peffers et al. (2008) proposed six defined activities for conducting design studies. We found that Peffers's six activity framework is straightforward and adaptable to developing a new programme and evaluating whether or not it may meet stakeholder demand. The framework offers a useful synthesized general model with the following steps: 1) identify problem; 2) define solution objectives; 3) design and development; 4) demonstration; 5) evaluation; and, 6) communication.

As mentioned earlier, our methodology is based on sequencing the above in three broad phases and is illustrated in Fig. 2. The first phase requires identification of education demands followed by artefact creation and evaluation (in this case, of the programme) before we identify outcomes and the communication of results. These activities are constructed in terms of Peffers et al. model, namely realising a problem situation (step 1); analysing published literature for gaps (step 2); developing a proposed course structure, and testing the course in practice via concept prototypes that were evaluated by senior academics, industry professionals, researchers and students, whose views were captured through semi-structured interviews (step 3); involving a proof-of-concept demonstration of the applicability of the proposed course structure, exploring potential commitment of these stakeholders (step 4); summative evaluation occurred with participant feedback and in student workshops (step 5); and, further proof-of concept findings and analyses of feedback received inform the communication of results in this paper (step 6). Table 2 explains how these activities are supported through the proposed three phases.

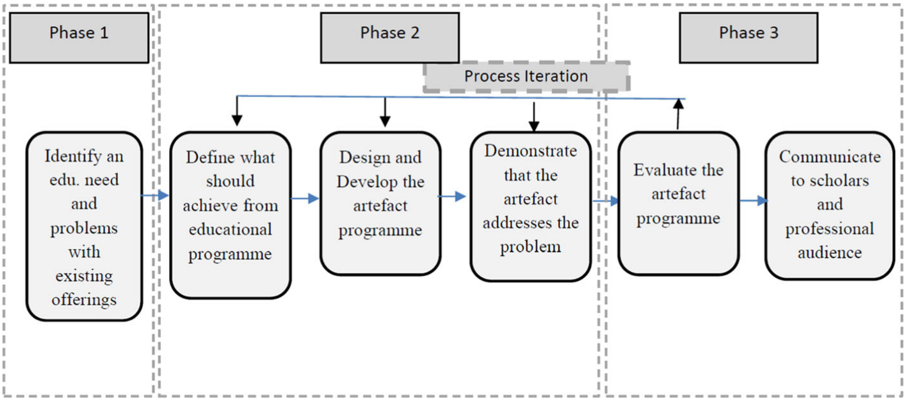

Fig. 2 The proposed three phase based DBR methodology

The six components of Peffers et al. (2008) DSR methodology are used as steps in the proposed three-phase DBR approach, ensuring iteration between phases 2 and 3. The iteration process provides a 'check point' for validity and relevance of the prototype proposed degree structure. Engagement of senior academics and industry professionals in phase 2 and 3 allowed us to evaluate the extent to which our findings supported our objectives (e.g. by allowing for specific subjects to be added or modified or removed from the degree structure) as a basis for replacing the existing degree offering. It is argued therefore, that our proposed three phased DBR approach complements understanding of DSR informed through a well-recognised methodology. Details of the phases are illustrated in Table 2.

4 Findings

Responses from different stakeholders indicated that the integration of business and latest technological knowledge in a holistic manner was limited within the current information systems management programmes at our university.[9] Neither industry professionals or senior academics were confident that current IS bachelor degree offerings met contemporary educational demands of industry and community. When interviewed, all of the participants were positive about the need to design a new business data science degree programme that might better align to current industry trends and future demands of employers for business graduates. Example responses and views are described below, aligned to the three different phases outlined earlier:

4.1 Identifying education needs

In response to the question of, *"What would you expect from a modern business IS bachelor degree",* senior academics expressed:

> "We are living in a rapidly data and information growing environment, organisations are seeking ways of having value from the data to understand their

[9] The research is conducted under the ethics approval bearing a reference number: Ref: HRE18–184

Table 2 Phases of the DBR methodology adapted from the Six Activity framework by Peffers et al. (2008)

Phases	DSR design activities	Our artefact design
identifying education needs and artefact types	Activity 1 and 2	There is a need to develop appropriate knowledge and skills for business graduates so that they can add value to organisations in analysing data for producing insights or meaning towards data-driven decision making. Many current education programmes in IS are not geared toward producing business data professionals such as data analysts for this purpose. This is the motivation for exploring the development of a new degree course that could address this industry need. Knowledge in data science, analytics and visualisation and statistics, mining and auditing skills are vital areas of focus but their alignment tends to be limited to mathematical, higher level statistics and computational engineering education.
artefact creation for solution testing and formative evaluation	Activity 3 and 5	Interdisciplinary approaches as employed in other domains were considered in the design of the proposed artefact (degree programme). The design process was iterative in order to capture insights related to perceived demand and relevance of programme subjects and topics. A prototype was developed as a fundamental and commonly-accepted design artefact, coupled to a case scenario analysis and subjected to formative evaluation in focus groups.
summative evaluation and communication of results	Activity 4 and 6	The proposed programme, theoretically informed through Owen's (1997) framework for loosely coupled interdisciplinarity was presented in a focus group setting, to academic and industry professionals who evaluated it for its perceived suitability, and to students for perceived value and preference. The findings are intended for peer review and scruitiny following the usual scholarly publication practice.

propositions and insights……organisations seek modern business graduates who can help them to make sense of data and help them current problems of businesses." (LiN_9N18)

"It is important to tailor our current offerings to reflect on the data driven practices in the industries, so that we may produce graduates who can better understand the languages in businesses in terms of data oriented decision, value of data from diversified sources for marketing, sales and product design… data sciences for businesses can give a niche area of modernising business information systems teaching pedagogy for knowledge growth and expansion for next generation. Universities have started offering courses on data analytics …" (OliB_2N18)

"Our business students will be the future generation business managers, they will require to get some meaning out of millions of databases that business organisations have produced and many of them are unstructured in nature, as they come from different sources such as online and other internal and external agents.

> Students must have adequate knowledge for analysing such unstructured data for creating new meanings or decision making for various purposes such as for product design, marketing and sales…"(MoR_1O18)

An industry professional expressed:

> "More and more technologies are coming for offering benefits to businesses, we need a new degree programme like other university such as … university and … university. I think our graduates should understand how to capture, process, analyse and present the data from various sources or in various form such as video, audio and text for business decision support…" (HiS_15N18)

These comments confirm that the use of analytics technologies is believed to be important for graduates, and that leading universities are already beginning to provide offerings of this type. The comments also support an argument for preparing students to, "Think with Data" (Hardin et al. 2015a, b, p.343).

4.2 Programme creation and evaluations

Participants' responses have also been taken into consideration in the proposed structure of the programme based on indicative quotes such as below:

> "... it is very important to employ an interdisciplinary approach so that business students can achieve understanding on data or latest posts on consumer diversity, collaborations and stakeholder participation and various technologies for improving business processes." (MR_1O18)
> "Industry requires to see expertise growth in a particular area such as marketing or supply chain, so I think course topic areas should capture any particular field for business data science oriented learning." (AlvM_2O18)
> "For undergraduate students I think students must have knowledge on how to clean up the data prior to their processing, because there are lot of matters and perspectives around the data, so they need to be put in a system for further analysis. So, I think knowledge or skills on data cleansing methods, techniques, tools or principles would be of paramount value for undergraduate students." (AlvM_2O18).
> "Industry may expect a broader level of data analytics knowledge and key concepts; they need a broader awareness and then at entry level position, if it is a technical role, familiarity with tools obviously for open sourced platforms, data analysis and source tools and some more familiarity with a kind of general context of businesses like marketing or financial type like financial services." (EdC_1O2018)
> "From a commercial perspective industry may need someone from a strategic side – it is important to translate requirements to technical people like analysts, they know what would be the solution (analytic) in the business end, they can create, it can be forced in project management, which is a vital aspect of learning …" (EdC_1O2018)

Such statements reveal specific curriculum areas seen to be important by different stakeholders, as well as the interdisciplinary required of the graduates.

4.3 Knowledge contributions and communication of the artefact

Reviewing the concept proposal for the new degree programme on respondent stated,

> "Yes, I think the proposed structure in its final form has got technical components, project management aspects and other fundamental essentials so that an overview of data I mean big data, data mining tech, modelling as well as decision making realities that cover the whole pipeline for the business end and technical aspects of education. …" (EdC_1O2018)

Revealing it drew initial positive evaluation by a representative stakeholder. Naturally, special interests and local expertise were reflected in suggestions, for example, in prototyping, one senior academic suggested a new unit on healthcare analytics so that graduates can learn or apply their practical knowledge into a specific domain. Our university, a significant provide of health and allied health disciplines will have a hospital on campus as a part of development in the region, and as health informatics is an emerging area of studies, it was suggested that a new unit can be beneficial for healthcare students. An industry professional also agreed with this.

Another professional said:

> "Students may need to have 'environment' so that they can look and feel for big data such as a cloud environment for data access platform because a stand-alone computing or pc environment may not be capable of handling this, a large server for processing data or students exercises for data processing with relevant tools – in the powerful lab plus a guest speaker on a regular basis for students support and bringing industry into the classroom …" (EdC_1O2018)

Such comments can be helpful, and indicate potentially optional aspects desirable in the programme but not necessarily core topic areas. With an interdisciplinary development group and good focus group facilitation the relative value of programmes as proposed here can be assessed in this way, and imaginative solutions developed for teaching delivery, elective streams, or concentrations that might accommodate special interests without compromising the core structure.

5 Outcome artefact: Proposed Programme structure

The current structure of the Bachelor of Business degree at Victoria University comprises 24 units of study including 7 units of specialisation, selection of elective units from a limited list in the school, professionally accredited against rules such as sequencing of units, pre-requisites, key body of knowledge topic areas, and policies encouraging utilisation of internal resources or allocation of appropriate resources and expertise for teaching and learning.

Within these constraints and adopting a DSR based approach we developed a new perspective and landscape to offer an interdisciplinary programme in data science, targeting business students with a tailored development in information technology, business statistics and analytics that matches industry and community requirements for a 'pure' business bachelor degree programme. The programme objectives emerged from the inputs of industry professionals and senior IS academics and one of the experience of one of the authors in data analytics research (Miah et al. 2019a, b; Miah et al. 2017; Miah et al. 2019a, b) and preparing graduates to pursue employment opportunities as Data analysts/translators, Business Analysts and Business Data Scientists. The proposed course is designed to equip graduates with an understanding of data-oriented challenges faced by organisations through concepts, best practice, tools and techniques for data analytics. Students would gain sound theoretical knowledge and hands on experience to find solutions for challenging problems in data curation, processing, storage and analytics. The proposed programme objectives are categorised into facets that align with contemporary job descriptions of business data scientists, data translators and business data analysts:

- *Basic data focused knowledge*: Business students should develop an understanding of the value of business data, analytical thinking, develop tools and techniques for generating meanings and data summaries through classification, clustering unstructured business datasets; be able to construct basic models of data for analysis; gain experience with pattern recognition and knowledge discovery techniques to establish data relationships; demonstrate data analysis techniques and simulations of phenomena of interest that assist in developing business operational and strategic matters.
- *Data analytics and technical skills*: Students should become familiar with modern open-source procedural languages to develop and maintain data analytics; learn high level tools to visualize data to gain insight into data relationships; understand the process and tools (such as languages R, Tableau, Python and NoSQL) supporting essential data analytics tasks, including extraction, cleaning, classification or prediction, and interpretation.
- *Business data science/business expertise:* Students should have knowledge about managerial decision making through data analytics approaches for solving practical business problems in the data rich environments of today and the future; understand how to interpret and predict analysis results and convey the findings using a variety of techniques to a general businessperson by applying statistical principles to collect, rectify, analyse and interpret data using analytical and computer-based techniques and applications.

These three board objectives are aligned with the MSIS 2016 competencies in the area of *Data, Information, and Content management* for pre-masters or bachelor degree course, which is outlined by the Joint ACM/AIS Task Force in 2016 (Topi et al. 2017). The competency area covers learning attributes that enable business graduates to be effective contributors in processes that improve the business domain's ability to achieve its outcome and objectives analysing and processing structured and unstructured data effectively (Topi et al. 2017). The high-level competency dimensions for graduates are related to:

1. Identify data management technology alternatives, select the most appropriate options based on the organizational or business information needs.
2. Identify, create, and manage organizational policies and processes related to data and information management such as regulatory requirements, ethical considerations and implications of decisions support techniques.
3. Analyse the needs in different organisational or business domain to determine how those needs can best be addressed with data driven management and relevant solutions.

The proposed programme structure communicates a minimum skill set necessary to understand, ingest, plan and make predictions on business operations in practice. This foundation provides the necessary understanding, views and knowledge to pursue a business-oriented data science bachelor degree programme, reflecting the insights and feedback generated from the experience of the participants described earlier. The proposed structure provides the fundamental concepts, knowledge and skills required to pursue a career development path as data analysts, business data scientists, data engineers, and data translators within the current and imagined global economy. The promise here, is to support the strategic use of data or data warehouses to facilitate data-driven business decision making. It is proposed that traditional business IS education will be superseded by this or this type of new programme, within which, the following teaching and learning units are imagined.

- Data Science and Concepts: Data science is a multifactorial area in which data science methods and principles are studied from a business practitioner point of view. The relevant topic areas are: data compilation, cleansing, preparation and modelling throughout the life-cycle of data science from basic concepts and methodologies to open source tools of data analysis. The unit will enable understanding and knowledge on how data scientists act upon the major steps involved in tackling various data processing problems for purposes such as forming a concrete business plans, or collecting and analysing data for model development using open sourced platforms such as R Studio.
- Business Decision Making and Analysis the unit provides fundamental concepts and theories associated with decision making support and analysis of information for managerial needs. The unit offers practical experience using case studies and illustrates a range of current modelling (such as data mining for business intelligence; text and web mining; artificial intelligence and expert systems) and data analysis tools such as models or methods of decision support, data analytics and business intelligence for enabling understanding of the process of decision making in organisations.
- DBMS: The data base management systems unit introduces structured and relational database design and implementation enabling concepts, methodologies, tools and techniques to analyse, design, and develop well-structured databases for modern organisations. Data modelling using NoSQL and SQL languages are used for DBMS implementation in case demonstration with data definition and manipulation.
- Big Data for Business: the unit will cover the five characterised components of big data or the '5 Vs': Volume, Velocity, Variety, Veracity and Value. With data sets

increasingly too large to store and analyse beyond the ability of traditional relational database technology, this unit is built around fundamental knowledge on big data technology and social media platforms for defining the core concepts behind big data problems, applications, and systems. It introduces the most common open-source software frameworks and their potential in applying data to transform our world.

- Business Analytics and Data Visualisation: As the use of big data becomes increasingly important to business, it is essential to be able to analyse data and provide meaningful decision support information in discovering new knowledge and supporting judgment and action plans. This unit provides students with advanced analytical methods and data mining models for ICT business analytics, as well as contemporary techniques to visualise the data for decision support. The content includes data preparation, association rule analysis, classification, clustering, regression, anomaly detection, building analytic models using NoSQL, R, and data visualisation.
- Supply Chain Analytics: This unit offers an application example in the development of knowledge in a practical field of supply chain and logistics management. The unit provides a variety of supply chain management situations and challenges that seek data-oriented solution designs, analytical and optimisation models, analytics around decision-support tools, and solution techniques. The key focus is on applying these analytical techniques to identify and resolve contemporary supply chain and logistics related business problems such as demand forecasting and automation.
- IT Profession, Ethics and Data Security: This unit articulates the role of the IT profession within local and global communities. The unit examines a wide range of ethical, security and privacy issues and concepts in ICT or data base management field. The unit develops student critical thinking and other enterprise skills by introducing topical and controversial issues related to computing ethics and privacy problems.
- Predictive Analytics Projects and Management: The advent of predictive analytics has resulted in businesses and governments processing and storing massive volumes of data for predicting unseen future opportunities in business growth and product maximisation. Organisations realise the potential insight this data can provide and are applying intelligent methods to process large 'big data' information repositories to support effective decision making. This unit will provide students with the knowledge and skills to utilise predictive analytics and data mining processes and technologies to gain greater insights into various business scenarios. Students may gain knowledge of foundational tools and techniques, supported by industry case studies and hands-on exercises.
- Applied Business Challenge: This unit focuses on the development, demonstration and application of student skills around the themes of leadership and challenge that provide a thematic link from the Business Challenge stream. The unit enables students to demonstrate their understanding of the business environment and the knowledge and skills required for professional practice. 'Live' IT projects are located and drawn from industry, in which students also will critically evaluate their personal and professional skills, knowledge and values, and how these can be used to support business in addressing data oriented challenges.

In the proposed programme, the first-year units are aimed at developing basic organisational and business decision support skills and technologies based on the expectations of business process innovations and data generation. The second year involves education both on data science and relevant analytics concepts, methods, models, applications and theories from different disciplines relevant to business processes, while the third year units involve procedural programming languages (for example, business programming is an essential skill for data science), and advanced skills and knowledge generation on various emerging relevant issues including industry-intensive or data-centre practical tasks and live projects (for further details see Appendix (Table 6)).

6 Evaluation

Venable et al. (2016) described summative and formative evaluation of design artefacts with target populations of users. As a part of summative evaluation, the artefact is demonstrated for its value and effectiveness in focus groups coupled to a case scenario analysis. We used a group of 5 IS students who have just completed a traditional IS bachelor degree programme, and who were now practicing in industry. We thought this cohort would be suitable for asking about the value of the new proposed programme as they having completed a basic IS bachelor degree they may differences in skills requirements in industry relation compared with their skill and knowledge acquisition at university.

Hevner et al. (2004) proposed five evaluation methods for evaluating designed artefacts (i.e. observational, analytical, experimental, testing, and descriptive), while Vaishnavi and Kuechler (2004) refer only to qualitative and quantitative evaluation processes. Under the five methods Hevner et al. (2004) also suggested techniques such as computer and lab simulations, field experiments, lab experiments, analytical processing, testing methods, case studies, survey studies, and field studies. Criteria such as usability are applied to evaluate the artefact under discussion here (see Table 5 for an overview). An evaluation process should be conducted during the development stage to understand the prospective problems (from the participant group shown in Table 3) and also after the development stage, as in the study reported in this paper.

Gregor and Hevner (2013) suggested that DSR artefacts must be evaluated for reliability, validity, and utility based on case study data used to inform the artefact design as a basis for further evaluation of, *"a new artefact in a given organizational context affords the opportunity to apply empirical and qualitative methods"* (Hevner and Chatterjee 2010, p. 271). The final evaluation involved a confirmatory focus group of four professionals, adopting the approach of Tremblay et al. (2012) in evaluating usability and efficacy of the proposed programme.

We applied the knowledge contribution framework proposed by Gregor and Hevner (2013) in this paper, with provision for four aspects by which DSR researchers may claim contributions to knowledge, such as improvement of the solution artefact, invention of solution artefact, routine design of the solution artefact, and exaptation of solution artefact. In this paper the authors proposed a new artefact informed by and informing existing issues and new demands from the industry and academe, while cognisant of the demands of the national regulator (the Tertiary Education Quality and

Table 3 Participant groups details

Participants	Description
Senior academics	Academics are university teachers who are involved in teaching and research within the field of Information Systems/technologies. Participant academics had a minimum of 10 years of working experience within the areas of information systems, business, management and other relevant cross-functional areas.
Industry professionals	Industry professionals were mainly business analytics professionals experienced in turning data into products, actionable insights and meaningful stories. The participant professionals hold over 10 years of experience in several business organisations, related to the design, delivery and execution of (technical and strategic) analytical solutions, such as marketing, strategy, and health and wellness intervention.
IS Students	Information systems (IS) student focus groups were drawn from the Victoria University having completed their bachelor degree in IS in the previous year. This participant group has sound knowledge about current industry demands and career importance through completed internships or other industry oriented programs and activities.

Standards Agency and the frameworks it oversees under the Higher Education Support Act (Australian Government 2003).

In our study, we employed a descriptive method to evaluate the qualities of the proposed artefact using Venable et al.'s (2016) framework for conducting the entire summative evaluation activities in our study, from a the new curriculum needing perspective. Table 4 illustrates the steps for evaluation.

Participants were shown a demonstration of how the programme would be beneficial, showing the need in industry, the demand for skilled and knowledgeable workers in this field, its applicability across business areas and its unique interdisciplinary focus. The curriculum was discussed showing how it built generally useful skills but also allowed focus in specific business areas through practical and theoretical projects of direct industry relevance. Participants were asked questions to achieve feedback on their current IS degree. The questions were: What do you think about your current course structure, would you see the existing course was good enough for your future career development? However, once participants were clear on what the programme comprised, further evaluative criteria followed as shown in Table 5.

Students anticipated that the proposed course would be useful in improving their attitudes about data science as a possible career choice, and considered the proposed

Table 4 Overall evaluation activities

Processes captured from the framework of Venable et al. 2016.	Description
(1) Explicate the objectives	Our aim was to capture students views on the proposed programme
(2) Choose the evaluation strategies	According to Hevner et al. (2004), we adopted the descriptive approach for evaluating the proposed programme
(3) Determine the properties to evaluate	We aimed to demonstrate the value of the proposed programme
(4) Design the individual evaluation cases	We described the case details and anticipated demand for such a type of degree programme through focus group discussions

Table 5 Evaluation outcome of confirmatory focus group

Criteria	Positive agreement? P1, P2, P3 and P4	Practitioner (P) comments
Comments about current offering	N N N N	"In the old structure, most of the business subjects and some of them are IT subjects so ……it didn't come as a whole for something that is modern.." (P1) "I think the current information systems management course structure is good and I hope this degree will be applicable with the job requirements but …..I think that it is sad that I finish this without doing on data sciences" (P4) "I would love to have learned more since I talked to you back, knowing that I should have skills that is applicable to get a job right after completing my degree" (P4) "The new offerings is having professional focuses and I think it will be really good for new students who will study the course as major in business data science… as I said I wish I had studied this ..Before I graduated but Yah ..it is ….that I missed" (P4) I think we missed analytics in the old course but the new course has it…it is an important skills as business needs analysing data skills for them …."(P2)
Usability The programme will be useful for the current trends in industry demands	Y Y Y Y	"… industry is looking for new knowledge, the current degree programme does not offer data analytics learning, which is important for businesses such as in business decision making." (P1) "It is important to understand the data analysis requirements in specific business areas… the knowledge is important for getting beyond the understanding of basic databases in industry, because most of the businesses nowadays have started handling unstructured data sets." (P2) "Sometimes I think the new students will be lucky as they are getting all new and modern stuff for their learning... the degree will be good for their demands in industry." (P3)
The proposed programme offers useful topic areas of knowledge relevant to practical practices in industries	Y Y Y Y	"… the offerings will be good for them, I wish I had this programme, it looks effective more towards practical and workable stuff." (P4) "When you are talking about any programming or coding a solution, data is the first thing that you need to understand, … the analysis techniques are the vital for businesses for processing huge data, so we need this for jobs…" (P1)

Table 5 (continued)

Criteria	Positive agreement? P1, P2, P3 and P4	Practitioner (P) comments
The proposed programme will be helpful for student employability	Y Y Y Y	"I can't see why the new programme will not add value to students as the new subjects would be focused on practical stuff and attractive contents required for business operations." (P4) "Industry needs more practical support as the ICT infrastructure is there for them and data management or admin becomes the key roles for them ... the new programme is all about IT support for data related management knowledge… it is good." (P3)
Efficacy Replacing the current bachelor degree would be a positive outcome.	N Y Y Y	"The programme seems to add a lot of new important modern subjects such as analytics and big data stuff that were missing, I would love to do if I am given an opportunity" (P4) "I can see students can get basic knowledge and how they can be advanced in data analysis and processing knowledge growing … the structure seems good for them." (P2) "Yes I can see it is a good change and students will benefit from the proposed degree." (P3, P2)
We can see the new programme may offer new knowledge and benefits to business industries	Y Y Y Y	"I can see the new students will have benefits of having new knowledge in data security or data ethics as well as on data analytics awareness." (P3) "Industry is looking for new or modern awareness … the new programme sounds like it has very recent content and can give understanding to students." (P3)
The proposed programme will improve student experience	Y Y Y Y	"Students will have opportunity to learn business programming in open sourced programmes for their experience and skills development which is required for businesses." (P2) "The content has good stuff such as data mining and machine learning which would be good for developing experience." (P3)
Any possible disadvantages of the proposed degree programme?	N N N N	"Maybe the degree should not focus too much on technologies rather than a good balance between business and business data related knowledge." (P4)

P (P1 to P4) = Participants; Y = Yes, I agree; N = No, I don't see

team-teaching methods as positively enriching their learning. It is clear that all stakeholder representatives were positive about the proposal. In addition, as the ACM and IEEE-Computer Society have a long history of establishing international curricular guidelines for undergraduate programs in information systems. We found that the CS2013 particular Body of Knowledge areas called *Data, Information, and Knowledge* (Computer Science Curricula 2013) is moderately related to our program structural model. Each unit of the structure is further organized into a set of data oriented knowledge which are summarized in the table in Appendix 1 (Table 6). We anticipated that the topics within these units will offer appropriate knowledge and skills to the graduates at the target case institution.

7 Discussion

Keeping curricula relevant to graduate employment opportunities and societal needs is an ongoing challenge in higher education. The precepts of the Design Science approach in Information Systems are well suited to innovation in pedagogical designs, with methods tailored to ensure both rigour and relevance, particularly in Design Based Research, the education specific variant of Design Science discussed in this paper. The paper introduced a new DBR approach for conceptualising an interdisciplinary course, bringing different perspectives on teaching, learning, and expected graduate outcomes of value to future students. Importantly, the proposed DBR approach goes beyond routine design and development, helping us understand some of the relationships between educational theory, the designed artefact and relevant in-house practices (The Design-Based Research Collective 2003). Our approach enabled prototyping a concept and evaluating it against practitioner expertise as well as testing an approach to curriculum design and development.

Current data science education literature has many examples of initiatives that include curricula, programmes, courses, as well as projects, however, these often emerge within the confines of traditional disciplinary silos, primarily within an engineering ethos where business application is left as a future if not conceptually alien ideal. Adding such courses from other disciplines to a traditional business programme may assume more mathematical background and interest than is comfortable to many students but does at least provide an opportunity for the IS faculty to design, from the ground up, an appropriate offering that bridges the skill-sets required and that develops internal coherence of curriculum and course materials. Additionally, multi-faculty offerings can lack motivated ownership, and be too topically incoherent to gain accreditation from discipline-focussed accrediting bodies, again motivating a design by established IS specialists to meet relevant qualification frameworks and professional body standards. As an inherently interdisciplinary field itself, IS crosses business and IT school curricula, working at their critical intersections as well as their embracing contexts.

For any technological developments, Lee and Baskerville (2003, p. 241) state that, "*The process of action research suggests that the ability of a theory to be generalized to a new setting could also depend on factors outside the theory itself* [and]... *there is a social process for testing, refining, and hence circumspectly generalising the theory to a setting where it was not previously developed or tested".* The proposed DBR approach is generalisable for similar, 'action research' like design purposes where the designed artefact discussed here is a conceptual design for a business-focused data science degree where DBR was the theoretical framework used to develop the artefact. The value of this type of design approach is important to support advancing sustainable course design by understanding and supporting educator design practice as articulated by Bennett et al. (2018), promoting effective approaches to design and the choices made by educators.

Our conceptual design of an introductory data science degree programme is interdisciplinary, inclusive of information technology, business information systems and management within a Business School, aimed to assist in producing graduates with data skills, knowledge, and analytics abilities that are a unique marriage of these industry *relevant and needed* practical and technical skills. The objective of the degree programme is to provide a strong learning pedagogy for meeting managerial and business aspects of data science. We have collected views on the initial structure of the degree programme and separately assessed the overall feasibility of the proposal in the context of Australian higher education. The prototyping approach with representative stakeholders, which is common in DSR, has been adapted within DBR applied for this study and has proved fruitful in finalising a design that can be taken to the next phase of the University's validation and accreditation process.

The study is positioned in the emerging field of Engineering Education Research. The study was designed for a single case organisational context to develop a proof of concept of the proposed DBR approach. The developed approach can be further applied in other areas for designing cross-functional degree programs. As higher education and the broader tertiary education sector grapple with issues of currency, relevance, and supposed digital disruption, it is timely to imagine how best to develop courses, bundled, unbundled or otherwise geared to meet industry and market relevance and demand. Taking a human centred, design led approach such as DBR may provide means by which some of this threats and issues might be addressed to the benefit of individual (student) and organisational performance, as well as meeting the contemporary demands of industry. Inevitably, this paper has focused broadly on the curriculum design as opposed to pedagogy on the assumption that underpinned by the latest research on the quality of student learning and learning gain, course developed in this way will go a long way to developing both discipline knowledge and understanding as well as the enterprise and personal capabilities required by industry.

8 Conclusion

This paper introduced a course development approach for designing and evaluating an interdisciplinary data science programme, as an initial proof-of-concept prototype. The proposed DBR approach can be seen as an application of DBS incorporating both practical and technical perspectives for designing educational artefacts. In particular the design is relevant to business disciplines, by enabling the required integration of expertise from both computer information and data sciences co-created from contemporary industries, student and senior academic representatives in business IS domains using an interdisciplinary approach, respectful of organisational policies and resources, and also bearing accreditation requirements. The proposal specified in this paper was evaluated using such representation and was favourably received, enabling progress towards implementation and adoption. A limitation is that the final evaluation of artefact success must await implementation (including the pedagogical considerations mentioned above), review and planning authority's analysis and approval and competitive marketplace acceptance. However, this paper has shown how a DBR approach can successfully help conceptualise promising educational artefact development and evaluation.

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Appendix

Table 6 Degree structure (Proposed structure of the programme is mainly based on all internal resources and modification of existing subjects in order to reduce extra costing of developing new subjects)

Bachelor of business data science		
The major provides the fundamental knowledge in terms of problems, constructs, concepts, methods, tools and models oriented skills required to become a graduate with a career in business data analysis, data management (e.g. business data scientists, data translators, business data analytics officers) in organisations as well as business data analytics project management meeting various demands in the global economy. The degree will educate students with business operational knowledge and to support the strategic use of data focused decision systems to optimise decision making within global and local organisations.		
	Semester 1	Key learning objectives
Elective	Business Ethics	• Improve business ethical understanding and relevant business contexts • Skills for addressing ethical issues globalised social and economic environment
Core	Business Statistics	• Improve statistical knowledge for applying into business operations • Skills in all standard statistical techniques
Core	Management & Organisational Behaviour	• Improve understanding of organisational behaviour and management theory • Skills in various theories such as human relations theory; individual behaviour/perception, and group dynamics
Core	Intro to Database Design	• Improve fundamental concepts of database design • Skills development in database design requirement analysis and solution concept developments
	Semester 2	
Core	Accounting Information Systems	• Improve basic knowledge of business information systems for accounting operations • Skills development on relevant theories and practices of recording and reporting of accounting data
Core	Information Systems For Business	• Improve knowledge on fundamental concepts, issues and benefits of business systems to organisations and individuals • Skills development for data management and productive reporting
Specialisation	Data Science and Concepts	• Improve knowledge on data science concept and its practices for business operation • Skills data analysis algorithms, data exploration, manipulation and data visualisation
Core	System Analysis and Design	• Improve knowledge on methods, tools and techniques used for business situation analysis • Skills development for business data systems design and development practices and tools
	Semester 3	
Elective	Unit of Choice	
Specialisation	Big data for business	• Improve understanding on components of business big data • Skills development on fundamental knowledge on big data technologies and social media platforms
Specialisation	Business Analytics	• Improve knowledge on analytics applications for processing data essential to analyse for providing meaningful decision support

Table 6 (continued)

Bachelor of business data science		
		• Skills development with advanced analytical methods and data mining models
Specialisation	Decision Making and Analysis	• Improve fundamental concepts and theories associated with decision support and analysis • Skills on using case studies and illustrating a range of current modelling (such as data mining for business intelligence or decision support systems)
	Semester 4	
Specialisation	Predictive analytics	• Improve knowledge of data prediction applying intelligent methods to process the large information repositories (Big data) • Skills development to utilise predictive analytics and data mining processes and technologies to gain greater insights into various business scenarios for future strategy development.
Specialisation	Database management system	• Improve understanding on structured and relational database design and implementation enabling concepts, methodologies, tools and techniques • Skills development on data modelling using NoSQL and SQL languages are used for DBMS implementations
Elective	Unit of Choice	
Elective	Predictive analytics Project Management	• Improve knowledge of businesses governance data processing for predicting unseen future aspects such as for business growth and product maximisation. • Skills development on conducting projects applying intelligent methods to process the large information repositories (Big data) to support effective decision making.
	Semester 5	
Elective	Unit of Choice	
Specialisation	IT Profession, Ethics and data security	• Improve understating of the role of the IT profession within local and global communities and issues of ethical, security and privacy issues and concepts in the business data management field. • Skills development on introducing topical and controversial issues related to computing ethics and data privacy problems
Core	Supply Chain Analytics	• Improve application development knowledge in a practical field of supply chain • Skills of solution design for data oriented supply chain management.
Specialisation	Applied Business Challenges	• Improve understanding on development, demonstration and application of student skills around the themes of leadership and challenge • Skills of developing personal and professional skills and critically evaluate to support business
	Semester 6	
Elective	Unit of choice	
Core	Work integrated learning	• Improve students practical experience • Skills development for exploring workplace context and identifying their individual roles as an active member within the organisation.
Elective	Unit of Choice	
Elective	Unit of Choice	

References

Asamoah, D. A., Sharda, R., Zadeh, A. H., & Kalgotra, P. (2017). Preparing a data scientist: A pedagogic experience in designing a big data analytics course. *Decision Sciences Journal of Innovative Education, 15*(2), 161–190.

Asamoah, D.A., Doran, D. & Schiller, S. (2018), Interdisciplinarity in data science Pedagogy: A Foundational Design. *Journal of Computer Information Systems*, https://doi.org/10.1080/08874417.2018.1496803.

Australian Government (2003) *Higher Education Support Act* Department of Education and Training, online https://www.education.gov.au/higher-education-support-act-2003-and-guidelines. Accessed 24 May 2019.

Bell, P. (2004). On the theoretical breadth of design-based research in education. *Educational Psychologist, 39*(4), 243–253.

Bennett, S., Lockyer, L., & Agostinho, S. (2018). Towards sustainable technology-enhanced innovation in higher education: Advancing learning design by understanding and supporting teacher design practice. *British Journal of Educational Technology, 49*(6), 1014–1025.

Carstensen, A. K., & Bernhard, J. (2019). Design science research – A powerful tool for improving methods in engineering education research. *European Journal of Engineering Education, 44*(1–2), 85–102.

Cassel, L. N. (2011). Interdisciplinary computing is the answer: Now, what was the question?, *ACM Inroads* (2:1), ACM, pp. 4–6.

Cleveland, W. S. (2001). Data science: An action plan for expanding the technical areas of the field of statistics. *International Statistical Review, 69*(1), 21–26.

Columbus, L. (2017). IBM predicts demand for data scientists will soar 28% by 2020. Forbes. Available from: https://www.forbes.com/sites/louiscolumbus/2017/05/13/ibm-predicts-demand-fordata-scientists-will-soar-28-by-2020/#7f2b3057e3bd. Accessed 24 March 24 2019

Computer Science Curricula. (2013). Curriculum guidelines for undergraduate degree programs in computer science, the joint task force on computing Curricula Association for Computing Machinery (ACM), IEEE Computer Society, URL: https://www.acm.org/binaries/content/assets/education/cs2013_web_final.pdf. Accessed 24 March 24 2019

Conway, D. (2010). The Data Science Venn Diagram, dataists, available at http://www.dataists.com/2010/09/the-data-science-venn-diagram/. Accessed 23 Feb 2019

Christian, R. (2018). Wesfarmers To Open Data Analytics Centre For Retail Growth. https://www.channelnews.com.au/wesfarmers-to-open-data-analytics-centre-for-retail-growth/. Accessed 20 Feb 2019.

de Villiers, M. R., & Harpur, P. A. (2013). Design-based research - the educational technology variant of design research: Illustrated by the design of an m-learning environment. In P. Machanick & M. Tsietsi (Eds.), *Proceedings of the south African Institute for Computer Scientists and Information Technologists Conference (SAICSIT '13)* (pp. 252–261). New York: ACM. https://doi.org/10.1145/2513456.2513471.

Design-Based Research Collective. (2003). Design-based research: An emerging paradigm for educational inquiry. *Educational Researcher, 32*(1), 5–8.

Dhar, V. (2013). Data science and prediction. *Communications of the ACM, 56*(12), 64–73.

Gregor, S., & Hevner, A. R. (2013). Positioning and presenting design science research for maximum impact. *MIS Quarterly, 37*(2), 337–355.

Hardin, J., Hoerl, R., Horton, N. J., Nolan, D., Baumer, B., Hall-Holt, O., Murrell, P., Peng, R., Roback, P., Lang, D. T., & Ward, M. D. (2015a). Data science in statistics curricula: Preparing students to "think with data". *The American Statistician, 69*(4), 343–353. https://doi.org/10.1080/00031305.2015.1077729.

Hardin, J., Hoerl, R., Horton, N. J., Nolan, D., Baumer, B., Hall-Holt, O., Murrell, P., Peng, R., Roback, P., Temple Lang, D., & Ward, M. D. (2015b). Data science in statistics curricula: Preparing students to "think with data". *The American Statistician, 69*(4), 343–353.

Hayashi, C. (1998). What is data science? Fundamental concepts and a heuristic example. In C. Hayashi, K. Yajima, H.-H. Bock, N. Ohsumi, Y. Tanaka, & Y. Baba (Eds.), *Data science, classification, and related methods. Studies in classification, data analysis, and knowledge organization* (pp. 40–51). Tokyo: Springer. https://doi.org/10.1007/978-4-431-65950-1_3 ISBN 9784431702085.

Herodotou, C., Rienties, B., Boroowa, A., Zdrahal, Z., Hlosta, M., Naydenova, G. (2017). Implementing predictive learning analytics on a large scale: The Teacher's perspective, proceedings of the Seventh International Learning Analytics & Knowledge Conference, March 13–17, 2017, Vancouver, British Columbia, Canada, pages 267–271.

Hevner, A. R. & Chatterjee, S. (2010). Design research in information systems: Theory and practice, Springer Science & Business Media, accessed from: https://www.springer.com/gp/book/9781441956521. Accessed 24 March 2019

Hevner, A. R., March, S. T., Park, J., & Ram, S. (2004). Design science in information systems research. *MIS Quarterly, 28*(1), 75–105.

ICS. (2018). Data Scientist Demand Expected to Explode by 2020, ICS Blog, URL: http://blog.infinity-cs.com/data-scientist-demand-expected-to-explode-by-2020. Accessed 10 Feb 2019.

Ivanitskaya, L., Clark, D., Montgomery, G., & Primeau, R. (2002). Interdisciplinary learning: Process and outcomes. *Innovative Higher Education, 27*(2), 95–111.

Jaafar, N. (2018). The Rise of the Data Scientist, URL: https://www.launchrecruitment.com.au/news/rise-of-data-scientist/. Accessed 20 Feb 2019.

Klein, J. T. (1990). *Interdisciplinary: History, theory, and practice* (p. 1990). Detroit: Wayne State University.

Koivisto, J. M., Hannula, L., Boje, R. B., Prescott, S., Bland, A., Rekola, L., & Haho, P. (2018). Design-based research in designing the model for educating simulation facilitators. *Nurse Education in Practice, 29*, 206–211.

Lake, K. (1994). Integrated curriculum. In School Improvement Research Series, Retrieved from http://www.nwrel.org/scpd/sirs/8/c016.html. Accessed 12 Feb 2019.

Lattuca, L. R., Voigt, L. J., & Fath, K. Q. (2004) . Does Interdisciplinarity c questions, *The Review of Higher Education* (28:1), the Johns Hopkins University press, pp. 23–48.

Lee, A. S., & Baskerville, R. L. (2003). Generalizing generalizability in information systems research. *Information Systems Research, 14*(3), 221–243.

Li, X., & Chu, S. K. W. (2018). Using design-based research methodology to develop a pedagogy for teaching and learning of Chinese writing with wiki among Chinese upper primary school students. *Computers in Education, 126*, 359–375.

Miah, S. J. (2008). An ontology based design environment for rural decision support, Unpublished PhD Thesis, Griffith Business School, Griffith University, Brisbane, Australia.

Miah, S. J., Vu, H. Q., Gammack, J., & McGrath, G. M. (2017). A big-data analytics method for tourist behaviour analysis. *Information and Management, 54*, 771–785.

Miah, S. J., Vu, H. Q., & Gammack, J. (2019a). A big-data analytics method for capturing visitor activities and flows: The case of an island country. *Information Technology and Management*, xx, 1–19, https://doi.org/10.1007/s10799-019-00303-2.

Miah, SJ., Vu, HQ, & Gammack, J. (2019b). A location analytics method for the utilisation of geotagged photos in travel marketing decision-making. *Journal of Information & Knowledge Management*, (in press), https://doi.org/10.1142/S0219649219500047.

National Research Council. (2002). Scientific research in education. In J. Shavelson & L. Towne (Eds.), *Committee on scientific principles for education research*. Washington DC: National Academy Press.

Norwich, B., & Ylonen, A. (2013). Design based research to develop the teaching of pupils with moderate learning difficulties (MLD): Evaluating lesson study in terms of pupil, teacher and school outcomes. *Teaching and Teacher Education, 34*, 162–173.

Nunamaker, J.F., Chen, M., and Purdin, T.D.M. (1991). Systems Development in Information Systems Research, *Journal of Management Information Systems, 7*(3), 89–106.

Owen, C. L. (1997). Design research: Base building the knowledge. *Design Studies, 9*(1998), 9–20 PII: S0142-694X(97) 00030–6.

Pearson, T. (2018). The eternal doubt of wiring a SAN, source: https://www.ibm.com/developerworks/community/blogs/InsideSystemStorage?sortby=0&page=19&maxresults=50&order=asc&lang=en. Accessed 20 Jan 2019.

Peffers, K., Tuunanen, T., Rothenberger, M., & Chatterjee, S. (2008). A design science research methodology for information systems research. *Journal of Management Information Systems, 24*(3), 45–77.

Porter, A. L., & Youtie, J. (2009). How interdisciplinary is nanotechnology? *Journal of Nanoparticle Research, 11*(5), 1023–1041.

Simon, H. (1996). *The sciences of the artificial* (3rd ed.). Cambridge: MIT Press.

Smit, E. M., & Tremethick, M. J. (2013). Development of an international interdisciplinary course: A strategy to promote cultural competence and collaboration. *Nurse Education in Practice, 13*, 132–136.

Starcic, A. I., Cotic, M., & Zajc, M. (2013). Design-based research on the use of a tangible user interface for geometry teaching in an inclusive classroom. *British Journal of Educational Technology, 44*(5), 729–744.

The Design-Based Research Collective. (2003). Design-based research: An emerging paradigm for educational inquiry. *Educational Researcher, 32*(1), 5–8 URL: http://www.designbasedresearch.org/reppubs/DBRC2003.pdf. Accessed 27 May 2019.

Topi, H., Karsten, H., Brown, S., Carvalho, J. A., Donnellan, B et al. (2017). MSIS 2016, Global Competency Model for Graduate Degree Programs in Information Systems, URL: https://doi.org/10.1145/3127597.

Tremblay, M. C., Hevner, A. R., & Berndt, D. J. (2012). Focus groups for artefact refinement and evaluation in design research. *Communications of the Association for Information Systems, 26*, 599–618 June 2010.

Vaishnavi, V. & Kuechler, W. (2004). *Design Science Research in Information Systems*, January 20, 2004; last updated: November 15, 2015. URL: http://www.desrist.org/design-research-in-information-systems/. Accessed 24 March 2019

Vaishnavi, V. and Kuechler, W. (2008). Design Science Research Methods and Patterns: Innovating Information and Communication Technology, Auerbach Publications, Boston, MA

van den Akker, J., Gravemeijer, K., McKenney, S., & Nieveen, N. (2018). *Educational design research*, (1st edn), URL: https://www.amazon.com/Educational-Design-Research-Jan-Akker/dp/0415396352. Accessed 24 March 2019
Venable, J., Pries-Heje, J., & Baskerville, R. (2016). FEDS: A framework for evaluation in design science research. *European Journal of Information Systems, 25*(1), 77–89.
Wang, F. and Hannafin, M.J. (2005). Design-based research and technology-enhanced learning environments, Educational Technology Research and Development, 53(4), 5–23
Way, T. & Whidden, S. (2014). *A loosely-coupled approach to interdisciplinary computer science education*, Semantic Scholar Publisher. https://www.semanticscholar.org/paper/A-Loosely-Coupled-Approach-to-Interdisciplinary-Way-Whidden/038ea4a26bea08d3c9bcab4118920d2e6761a7c4. Accessed 24 March 2019.
Wolcott, M. D., Lobczowski, N. G., & Lyons, K. (2019). Design-based research: Connecting theory and practice in pharmacy educational intervention research. *Currents in Pharmacy Teaching & Learning, 11*, 309–318.