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Visual Analytics: Transferring, Translating and Transforming Knowledge from Analytics Experts to Non-technical Domain Experts in Multidisciplinary Teams

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Abstract

Today's complex problems call for multidisciplinary analytics teams comprising of both analytics and non-technical domain (i.e. subject matter) experts. Recognizing the difference between data visualisaion (DV) (i.e. static visual outputs) and visual analytics (VA) (i.e. a process of interactive visual data exploration, guided by user's domain and contextual knowledge), this paper focuses on VA for non-technical domain experts. By seeking to understand knowledge sharing from VA experts to non-technical users of VA in a multidisciplinary team, we aim to explore how these domain experts learn to use VA as a thinking tool, guided by their knowing-in-practice. The research described in this paper was conducted in the context of a long-term industry-wide research project called the 'Visual Historical Atlas of the Australian Co-operatives', led by a multidisciplinary VA team who faced the challenge tackled by this research. Using Action Design Research (ADR) and the combined theoretical lens of boundary objects and secondary design, the paper theorises a three-phase method for knowledge transfer, translation and transformation from VA experts to domain experts using different types of VA-related boundary objects. Together with the proposed set of design principles, the three-phase model advances the well-established stream of research on organizational use of analytics, extending it to the emerging area of visual analytics for non-technical decision makers.

Keywords Analytics · Data visualization · Visual analytics · Non-technical decision makers · Action Design Research (ADR) project · Visual Historical Atlas of the Australian Cooperatives (VHAAC)

1 Introduction

Over the past decade, the Business Analytics (BA) field, also known as Business Intelligence & Analytics (BI&A) (Chen et al., 2012), has undergone an important shift. While in the past the main users of analytics technology were data scientists and IT professionals, these days there is a greater emphasis placed on self-service analytics for non-technical decision makers (Stodder, 2020). This is because domain experts, also known as subject matter experts, have the necessary domain knowledge and expertise to make sense of contextual data and turn them into value-adding insights. This shift, in turn, accelerated non-technical decision makers' use of data visualization and visual analytics, as the new generation of analytics that does not require data science or IT backgrounds.

Thus, rather than just 'consuming' reports prepared by data scientists as they did in the past (Stodder, 2015), non-technical domain experts now have access to easy-to-use data visualisation tools that enable them to analyse data in a more intuitive way, driven by the problem-at-hand. Indeed, for today's managers operating in data intensive environments, "the only way to make sense of large data sets is through data visualization" (Berinato, 2016, p.1). Through an ongoing process of interactive visual data exploration,

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they also keep discovering new questions along the way (Swoyer, 2013).

However, the term ‘data visualization’ (DV) is frequently reduced to mean static visual representations of numerical data (i.e. visual outputs) in the form of graphs or charts (Berinato, 2013a; Stodder, 2013). As Berinato (2016) explains, ‘[i]n some ways, ‘data visualization’ is a terrible term. It seems to reduce the construction of good charts to a mechanical procedure. It evokes the tools and methodology required to create rather than the creation itself.’ (p.16). Consequently, DV tends to emphasize data and DV tools and applications.

Similarly, the related term ‘visual analytics’ (VA) also interpreted in a variety of ways by different communities. On one side, data scientists use the term VA to describe specialized applications of advanced data analytics, such as those in machine learning and neural networks, used to visualize model execution (cf. Hohman et al., 2019; Yuan et al., 2021). On the other hand, when used by non-technical business decision makers VA is understood to combines visualization with new practices for analytical reasoning and test-and-learn inquiry through interactive data exploration and discovery (LaValle et al., 2010; Stodder, 2013).

While acknowledging different interpretations, in this paper we focus on VA for non-technical users and consider it to *include* interactive DV. Thus, we define VA as a *process* of interactive visual exploration by non-technical decision-makers with domain expertise and contextual knowledge necessary to make sense of data, gain valuable insights and take data-informed actions. This interpretation corresponds to Stodder’s (2013) notion of ‘visual analytics’ and Berinato’s (2016) “discovery-focused exploratory visualization” (Berinato, 2016, p.5). Used as a verb (i.e. a process of visualization) rather than a noun (i.e. visual outcome) as in DV, *visualisation* is thus interpreted here as intuitive and open-ended. Understood in this way, VA shifts the focus from tools, visual outcomes (e.g. graphs and charts) and even data themselves, to the process of sense-making through visual exploration of data, in a given context and by domain experts from any organizational level (not just executives).

While the industry demand for DV and VA tools is rapidly growing (Berinato, 2013b), industry practices are still limited by the lack of skills among non-technical users (Stodder, 2020). Thus, “[t]he greatest concern centers on whether employees will have adequate knowledge and skills to make effective use of the tools” (Stodder, 2013; p.5). As Berinato (2013a, b) notes businesses need insights “not just pretty pictures” (p.1).

Moreover, to deal with increasingly complex problems, organizations are now building multidisciplinary analytics teams, which include analytics experts and non-technical subject matter experts (Davenport, 2020; Talagala, 2019; Zhang, 2019). As Hindle et al. (2020) note “analytics is a multidisciplinary endeavour” (p.489). Teams are also created in response to the previously-held unrealistic expectation about the all-encompassing knowledge and skills of data scientists and other analytics experts, which were expected to span data science, IT and business (Baskarada & Koronios, 2017; Baumeister et al., 2020; Zhang, 2019).

However, organizations building teams around VA are now faced with a new kind of knowledge gap. On one side there is a VA expert with an in-depth understanding of analytical tools and techniques but lacking domain and contextual knowledge necessary for visual data exploration and interpretation. On the other side, there is a decision-maker, with a domain knowledge and contextual understanding of data, but lacking VA expertise, which involves more than data visualisation. At the same time, the tacit knowledge (Polanyi, 1966), which is involved in visual data exploration *process*, makes it very difficult, if possible at all, for a domain expert to articulate, let alone delegate this process to a VA expert. Although not in the same domain and thus outside of the scope of this paper, a similar scenario would be a medical expert exploring and making sense of visual data in a particular context, versus VA or DV expert looking at the same data without any medical expertise.

The need for further research on transfer of knowledge from analytical experts (i.e. data scientists and IT experts) to domain experts has been recognized by other researchers such as (Holzinger, 2016; Benbya et al. 2021). We aim to contribute to closing this research gap by focusing on a method of VA-related knowledge sharing from VA experts to domain experts in multidisciplinary teams. Guided by the stated differences between VA and DV, we recognise the role of a VA expert to be different from that of a DV expert. While a DV expert predominately focuses on data visualisation, the skills and competencies of a VA expert are much broader and include other aspects of visual analytics, such as data modelling, data quality process as well as design and implementation of a data exploration environment.

In framing of our research, we also recognize that the research problem of knowledge sharing in general, including knowledge transfer, has been investigated by the knowledge management (KM) field for decades – see for example Nonaka (1994), Alavi and Leidner (2001), Malhotra (2004), Newell (2014). However, analytics opens new challenges for KM (Pauleen & Wang, 2017; Tian, 2017), including sharing of analytical insights (Marjanovic, 2021). We extend this line of thinking to visual analytics, in particular to the challenge of VA-related knowledge sharing between VA experts and domain experts, which is yet to be investigated by the analytics, VA, KM and Information Systems (IS) communities.

Against this background, this research aims to investigate on the following broad research question: *How to effectively* *facilitate sharing of VA-related knowledge between VA experts and non-technical domain experts in multidisciplinary VA teams*? We are particularly interested in new VA-specific methods for sharing of tacit knowledge across disciplinary boundaries that go beyond co-design of visualisations (i.e. visual outputs such as dashboards), which is a quite common organisational practice.

The research described in this paper was conducted in the context of a long-term industry-wide research project called the 'Visual Historical Atlas of the Australian Co-operatives' (VHAAC) project (Patmore et al., 2020, 2021, 2022) . This national, large-scale project, funded by the Australian Research Council, was implemented over four years (2017–2020) by a multidisciplinary team comprising of VA experts with expertise in design and implementation of interactive VA environments, including data collection and modelling and domain experts with expertise in the history of the Australian Co-operatives, labour history and historical research methods. The project included design and implementation of the VHAAC environment – an industry-wide, online interactive visual data exploration environment of the Australian cooperatives, ranging from the 1820s to today. Now in its sixth year, the VHAAC environment is the most authoritative source of data on the Australian cooperatives to date.

Within this context, VA-related knowledge sharing between the VA experts and the domain experts was critical for the success of the VHAAC project. However, this knowledge sharing went beyond the common practice of co-design of various visualisations. Instead, its main objective was to empower the domain experts to use the VHAAC as an interactive, visual "thinking tool" (Thorp, 2013), guided by their knowing-in-practice (Orlikowski, 2002). The VHAAC environment thus provided an opportunity as well as created a necessity for a practice-inspired research project described in this paper.

To answer the stated research question, we conducted an action design research (ADR) project which resulted in an innovative method for knowledge sharing based on VA boundary objects. Informed by prior research on secondary design (Germonprez et al., 2011; Lakew & Aryal, 2015), we recognized VA experts as the 'primary designers' and domain expert users of VA as 'secondary designers' engaged in design-in-use. To emphasize and honour their principal role in visual data exploration, we renamed *secondary* into *principal* designers.

The paper thus proposes a method of VA-related knowledge sharing between *primary* and *principal* VA designers. The method is theorized as a as a three-phase process of knowledge *transfer*, *translation* and *transformation*, which each phase using a different type of VA-specific boundary objects (BOs). Phase 1 includes syntactic BOs in the form of static data visualisations (i.e. visual representations) and data-driven stories. Phase 2 includes semantic BOs in the form of co-created problem-driven visual stories and an exemplary external visual exploration environment used for collaborative future imagining. Phase 3 resulted in the visual data exploration environment (i.e. the VHAAC) itself becoming a pragmatic BO, which in turn enabled decision-makers to shift the focus from data to seeing and thinking 'through data'. In addition to the proposed method of knowledge transfer, another type of ADR design knowledge includes a set of design principles related to VA boundary objects and their use.

This research offers several theoretical and practical contributions to the field of Information Systems (IS), at the intersect of analytics or more precisely VA, and knowledge management (KM). First, our research addresses the previously observed research gap related to the transfer of knowledge from analytics to non-technical experts (Holzinger, 2016; Benbya et al. 2021), which we investigate in the context of VA for non-technical decision makers. We also demonstrate that knowledge transfer is not sufficient and needs to be expanded with knowledge translation and transformation. Second, we also advance the the current research on BA by focusing on still under-researched VA for non-technical domain experts. We highlight the critical role of their domain knowledge for data exploration and sense-making in VA. In doing so, we extend the previous finding by Ghasemaghaei et al. (2018) about the importance of domain knowledge in analytics. Third, our research expands the well-established KM research on organizational knowledge sharing processes (Alavi & Leidner, 2001; Nonaka, 1994) to the emerging stream of research on VA. In particular, we explore the process of VA-related knowledge sharing in multidisciplinary teams at a very granular level and through the use of different VA-related boundary objects.

In terms of practical contribution, we propose a method that we developed, refined and evaluated-through-use in our own large-scale industry-wide VHAAC project, now for six years. We also explain how the same method could be adopted and further refined by other multidisciplinary teams in different contexts, aiming to better leverage tacit knowledge of their non-technical decision makers.

The paper is organized as follows. Section 2 describes the related work and builds the necessary foundations. Section 3 introduces our research context while Section 4 outlines our adopted Action Design Research Method (ADR). Section 5 describes the combined theoretical lens of boundary objects and secondary design, which we used as ADR kernel theories. Section 6 presents three groups of VA-related boundary objects (syntactic, semantic and pragmatic) and explains how there were used to facilitate knowledge sharing in our multidisciplinary team. Section 7 answers the research question by theorizing a three-stage method for knowledge transfer, translation and transformation from VA experts to domain expect. The proposed method is accompanied by a set of ADR Design Principles articulated in Section 8. Section 9 summarizes the main theoretical and practical contributions while Section 10 concludes the work by discussing study limitations and future opportunities for research.

2 Literature Review of Related Work

2.1 Foundation Concepts: Data Visualization and Visual Analytics for Non-technical Decision Makers

Data visualization applications are widespread and used in very diverse disciplines such as journalism, social sciences, medicine, engineering, feminist data studies, communication, business, information design, data science, analytics and information systems, see (Kleim et al. 2008; Baker et al., 2009; Dilla et al., 2010; Dilla & Raschke, 2015; Few, 2006, 2012; Thorp, 2013; Hill et al., 2016; Gatto, 2015, Camm et al., 2017). Across these disciplines, DV is commonly used to enhance the user's understanding of quantitative and textual data (Few, 2006; Tufte, 1983). For many organisations, this is the primary reason why they continue to invest in DV tools (Franks, 2013). DV's explanatory power is further increased when combined with storytelling (Kosara & MacKinlay, 2013; Watson, 2017).

Considered to be different from DV, visual analytics (VA) emphasizes visual data discovery process, including the observable and ongoing feedback (Stull-Lane, 2021). User-driven data exploration, made possible by VA, is vastly overlooked by organizations still focused on DV (Franks (2013; Stodder, 2020), often in the form of pre-programmed dashboards developed to meet user requirements. As Stodder (2020) explains: "In the best case, developers have interpreted what users want and have produced applications that are stable and allow for incremental adjustments, such as to visualization styles" (p.22). Yet, visual data exploration by domain experts is very different in nature and cannot be captured in its entirety by user-requirements.

In essence, DV and VA conceptualize 'visualization' respectively as *an outcome* (i.e. visual representation) or as *a process*. As Thorp (2013) explain, "by thinking about visualization as a process, instead of an outcome, we arm ourselves with an incredibly powerful thinking tool" (p.1). This process view of visualization, emphasized by VA, also reflects the complex and knowledge-intensive nature of decision-making by subject matter experts, which includes experimentation, simulation, scenarios planning and evaluation (Stodder, 2013, 2015; Thorp, 2013).

By seeking to understand the knowledge sharing from VA experts to non-technical users of VA, we aim to explore how these domain experts learn to use *VA as a thinking tool* (Thorp, 2013) rather than a visual outcome of DV. A process of visual data exploration is thus guided by their ongoing discovery of new data insights, which in turn leads to new questions being asked. As such, this process is very different from knowledge sharing that occur during collaborative design of data visualisations, based on elicitation of user requirements.

2.2 Prior Studies on VA for Non-technical Decision Makers

Our literature review shows the prominence of VA-related research in data science and computer science. In these studies, VA refers to advanced visual data analytics applications used by data scientists and IT professionals in various contexts. For example, VA systems of this kind are now used in machine learning, neural networks, data mining, computer graphics and computational data science – see (Hohman et al., 2019; Andrienko et al., 2020; Yuan et al., 2021). Their shared objective is to visualize executions of models and algorithms in order to support their improvement and explanation. While these developments represent an important direction in the emerging field of VA, in this paper we focus on a fundamentally different interpretation of VA as discussed above, and its use by non-technical subject matter experts.

In comparison to a much larger body of VA-related literature in data science and computer science, research on VA for non-technical decision making is nascent but starting to emerge. This could be explained by a quite recent shift to self-service analytics and the emergence of DV tools for business users (Stodder, 2020).

In this very-limited body of research on VA for non-technical decision makers, we observe recent studies on interactive data visualization (IDV), which we consider to be included in VA. Conducted across different disciplines, these studies focus on the effectiveness of IDV in decision making. For example, Perdana et al. (2018) studied the role of IDV in accounting and found that it can enhance the ability of non-professional investors to make sense of financial statements. Gurdal et al. (2017) focused on strategic management knowledge acquired by visual mining and analysis of existing knowledge on profit patterns. Other researchers, such as (Dilla et al., 2010; Dilla & Raschke, 2015; Huber et al., 2018; Phillips-Wren & McKniff, 2020), found that IDV improves decision-makers' perceptions, decisions and impact in various contexts, from finance to healthcare operations. These studies highlight the importance of experiential knowledge of non-technical decision makers (Freeze, 2018).

Instead of focusing on decision making by non-technical subject matter experts and its effectiveness, in our study we shift the focus to the process of acquisition of VA-related skills. In particular, we aim to investigate how these skills are aquired through knowledge sharing from VA experts to non-technical domain experts, which we review next.

2.3 Prior Studies on Knowledge Sharing from Analytics Experts to Non-technical Domain Experts

Decades of knowledge management (KM) research offer numerous studies on knowledge sharing. Particularly relevant are those related to sharing knowledge across boundaries, such as those conducted by Nonaka (1994), Alavi & Leidner (2001), Malhotra (2004) and Carlile (2004). Based on Polyani's (1966) research into tacit and explicit knowledge, we recognize that visual data exploration by domain experts draws upon their tacit knowledge, which includes both subject matter expertise and contextual understanding. Unlike explicit knowledge, tacit knowledge cannot be easily externalized, let alone described to another person. Therefore, this knowledge cannot be codified in order to be transferred across knowledge boundaries (Malhotra, 2004; Alavi & Leidner, 2001). Instead, it is drawn through problem-solving and action taking.

We recognize the problem of knowledge sharing from VA experts to domain experts, as the KM problem of sharing of VA-related tacit knowledge (Malhotra, 2004; Nonaka, 1994). Moreover, the process of sharing itself is knowledge-intensive in nature (Alavi & Leidner, 2001), and consequently, very complex. Nonaka (1994) theorizes that 'tacit to tacit' knowledge transfer process requires externalization followed by internalization knowledge. Given that tacit knowledge cannot be easily externalized, it cannot ever be transferred in its entirety.

Sharing of tacit knowledge between VA experts and domain experts is made even more complex by the existence of disciplinary boundaries. Consequently, these experts cannot easily collaborate as even lack the shared vocabulary, let alone any shared foundations. Differences in meaning and disciplinary understanding across knowledge boundaries, therefore, require knowledge translation, which is more complex than knowledge transfer (Carlile, 2004). Moreover, the respective natures of the disciplines on different sides of the shared knowledge boundary also play an important role. For example, in the case of our project, these disciplines were based on very different methods of inquiry—analytical used by VA experts and historical used by domain experts. We note that this particular aspect of knowledge sharing across disciplines is less explored in the previous literature, and yet to be researched in the context of VA-related research.

Our literature review also confirms that BA introduces new challenges for KM, as discussed by (Marjanovic, 2021; Pauleen & Wang, 2017; Tian, 2017). Prior studies considered sharing of knowledge among non-technical domain experts who were using analytics in the same organizational context – see for example Marjanovic (2021). These domain experts also came from the same disciplines. Consequently, they shared both contextual and disciplinary knowledge. Yet, knowledge sharing among them was not easy to achieve.

Particularly relevant for our project is prior research on transfer of knowledge from analytics to non-technical experts (Holzinger, 2016; Benbya et al., 2021), esspecially when working in multidisciplinary teams. This is increasingly the case as organizations are now building multidisciplinary analytics teams to tackle complex BA problems (Davenport, 2020; Hiltbrand, 2021; Hindle et al., 2020; Talagala, 2019; Vidgen et al., 2017; Zhang, 2019). As Vidgen et al. (2017) observe, to make analytics insights actionable it "takes more than simply setting up a data science team" (p.635).

However, as Stodder (2020) reports in a recent survey of analytical leaders, collaboration and knowledge sharing in these analytics teams are very challenging. In particular, there is a need for further research on knowledge transfer from analytical experts (i.e. data scientists and IT experts) to business and other non-technical experts (Holzinger, 2016; Abbasi et al., 2016; Benbya et al., 2021; Davenport, 2020). We situate this research gap in the context of the emerging discipline of VA by focusing on the following research question: *How to effectively facilitate sharing of VA-related knowledge between VA experts and non-technical domain experts in multidisciplinary VA teams?*

We are particularly interested in new VA-specific methods for sharing of tacit knowledge across disciplinary boundaries. In the next section we turn our attention to our broad and specific research contexts.

3 Research Context

3.1 Industry Context: Australian Cooperative & Mutual Enterprises (CMEs) Industry Sector

Across the world cooperatives continue to play a very significant economic and societal role in the lives of over one billion members and their communities, from all geographical regions and industry sectors (EURICSE-ICA, 2020; ICA, 2021a). Cooperatives are member-owned businesses (both for profit and non-for-profit) that are purpose driven and member-oriented (BCCM, 2019, 2021). They are 'original social enterprises', where members (e.g. employees, other businesses, community stakeholders), "work together to achieve a common purpose or outcome", and where the resulting value is shared among their members and communities (BCCM, 2013 p.1). Governed by a clear set of principles, they are are a form of economic democracy, with their democratic nature being the point of strength (Patmore & Balnave, 2018).

Throughout their long history, cooperatives have also shown to be the most resilient type of enterprise during previous periods of major crises – see for example (Birchall & Ketilson, 2009; Birchall, 2012; Roelants et al., 2012). The most recent Covid-19 pandemic crisis is no exception (Billiet et al., 2021; Mohit, 2021). This is due to their "business model that embraces the goals promoted by the 2030 Agenda in terms of human rights, fair labour, environmental sustainability, and sustainable growth". (ICA, 2021b, p.4).

In the Australian context, where our research is situated, there are currently more than 2000 Cooperatives and closely-related Mutual Enterprises (CMEs) whose combined membership base exceeds 29 million (BCCM, 2021). In the most recent financial year, the total revenue for the top 100 Australian CMEs was AUD 32.8bn dollars, with combined assets of AUD 1.2 trillion (BCCM, 2021). This is in spite of devastating bush fires and the still-unfolding COVID-19 crisis. In the 2021 financial year (i.e. the second year of global pandemic) this industry sector "directly employed at least 70,000 Australian workers and facilitated employment of 180,000 people" (Morison, 2021, p.1).

In spite of their significance, cooperatives worldwide continue to experience major challenges. "Despite there being over a billion members of the cooperatives worldwide", Cooper et al. (2013) observe, "they are not well understood, nor given much attention by academia or general public" (p. 6). The same observation applies to the Australian cooperatives (Balnave & Patmore, 2012; The Australian Senate 2016; BCCM, 2021). For example, while a significant proportion of Australians are members of cooperatives, very few are aware of their membership or can even name a cooperative enterprise (Australian Institute, 2012). Close to a decade later, despite its size and contribution, this industry sector remains "relatively poorly understood" (BCCM, 2021, p.4).

Responding to the urgent "need for the sector to build a stronger public awareness of its prominence and importance" (Australian Institute, 2012, p.12), the Australian Federal government initiated and conducted a Senate Inquiry into the economic and societal value of the Australian cooperatives (The Australian Senate, 2016). The outcome of this Inquiry included a number of key recommendations. Specifically, *Recommendation 1* articulated the need for national data on this important industry sector (Australian Senate, 2017, p.2). This particular recommendation provided the main motivation for our (broader) research project described next.

3.2 Our Broader Research Project: Visual Historical Atlas of the Australian Cooperatives

Inspired by the pressing need of the Australian cooperatives industry sector to increase its profile, both locally and nationally, we initiated a large-scale, long-term project focused on design and implementation of an industry-wide, online visual data exploration environment called the 'Visual Historical Atlas of the Australian Co-operatives' (VHAAC) (Patmore et al., 2020, 2021, 2022). The main idea was to enable different non-technical stakeholders to learn about the past and present of the Australian cooperatives from the 1820s to today. The co-authors of this paper have been the co-leaders of the project since its inceptions in 2017, and the core members of a wider multidisciplinary team.

Now in its sixth year, the VHAAC contains the historical data of over 7000 cooperatives, from 2,304 locations, (reference blinded for review) with four major types including agricultural, community, consumer and financial co-operatives. The data have been collected, verified, transformed, modelled and uploaded into the VHAAC visual database through an *ongoing* process conducted by the multidisciplinary team. Both qualitative and quantitative data have been collected by the team members with expertise in Australian cooperatives and verified using historical methods.

In addition to data, the VHAAC provides an easy-to-use visual data exploration environment for non-technical cooperatives experts. In fact, the main value of the VHAAC environment is considered to be in new insights gained by domain experts with expertise and experience necessary to understand both historical and contextual significance of data being explored. This use of the VHAAC is already advancing the cooperatives industry and research by providing new insights, informing the practice and challenging some historical misunderstandings. Examples include new findings about the longevity of cooperatives, reasons for their demutualization, their resilience in the face of different disasters, new insights into the reasons why they close, the identification of previously unrecognised types of co-operatives, the emergence of new types of digitally-enabled platform cooperatives, and the magnitude of their economic and societal importance in Australia from the 1820's to today (Patmore et al., 2021, 2022).

The project reported in this paper was conducted within the broader VHAAC project as its critical component that enabled the multidisciplinary team to continue to work together since its inception to today. Thus, very soon after the initiation of the VHAAC project it became clear that the multidisciplinary team faced a challenging knowledge barrier. On one side of this barrier were VA experts with holistic analytics expertise, which included data modelling, all aspects of design and implementation of interactive visual environemnts as well as DV but with limited understanding of the Australian cooperatives industry sector. On the other side were domain experts who were the main intended users of the VHAAC. The initial pilot project confirmed that a "standard" skill-based training focused on a particular VA tool used for development of the VHAAC was not effective (Marjanovic, 2016). This is because the skilled based

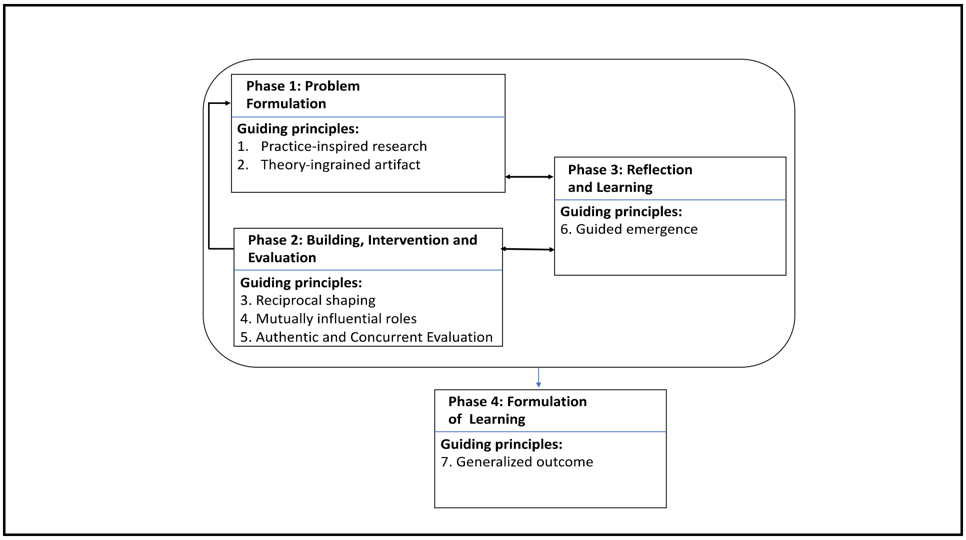

Fig. 1 Action Design Research (ADR) method, after Sein et al. (2011)

training focused on technical feature of the tool, as well as design of visual outputs (i.e. visualisation as a noun). Instead, the primary focus of these domain experts was not on underlying technology but on exploration of data for variety of known and yet-to-be discovered purposes (e.g., to influence, find similar co-operatives, engage in a future dialog and policy making process and so on). Moreover, the VHAAC environment was constantly emerging through data collection as well as our shared experience of design-in-use, knowing-in-practice and knowledge sharing. This in turn prompted the multidisciplinary team to engage in a meta-level project focused on a new method for knowledge sharing from VA experts to domain experts, which is reported in this paper.

4 Research Method

In this project we used the Action Design Research (ADR) method (Sein et al., 2011). This method recognizes and conceptualizes "the research process as containing the inseparable and inherently interwoven activities of building the IT artefact, intervening in the organization and evaluating it concurrently" (Sein et al, 2011, p.1). ADR was originally proposed by Cole et al. (2005) with the two key objectives: (i) to use valid scientific research methods to solve (a) practical problem(s) experienced by the researcher/practitioner; and (ii) to contribute to the existing body of knowledge in relevant areas by creating new design artefacts.

ADR draws its origins from two research methods: Action Research (AR) and Design Research (DR), also known as Design Science Research (DSR). By proposing to combine AR and DR, Cole et al. (2005) argued that an integrated approach is required to emphasize the research relevance, problem solving through intervention in the real-life setting, reflection and learning (Baskerville & Wood-Harper, 1998). as well as knowledge created through design (Hevner et al., 2004).. It is important to note that ADR is more than a combination of the original AR and DR methods (Sein et al., 2011). In ADR the phases of building, intervention and evaluation (BIE) of a design artifact are not separated as in DR, but highly intertwined. A combined learning and reflection phase is an important phase of ADR, that is not separate but constantly emerging through BIE. Finally, ADR recognizes different kinds of design artefacts, including IT systems as well as organizational interventions.

Both DSR and ADR have been used for design and implementation of DV and VA tools – see for example Toreini et al. (2021). However, in this project we shift the focus from design of VA tools to design of an innovative method for knowledge sharing from VA experts to domain experts, who are making sense of data through interactive visual data exploration thus using VA on their own and as a thinking tool. Therefore, the main intended ADR design artefact in our research is not a VA technology, but a knowledge sharing *method* across disciplinary boundaries in a multidisciplinary team.

Our research project followed the ADR phases (Sein et al., 2011) depicted by Fig. 1 and implemented them as follows. The project was initiated to address a problem identified in a real-life setting experienced by the co-authors who were the leaders of the multidisciplinary team of VA experts and domain (cooperatives) experts.

Therefore, our research was practice-inspired (Principle 1) as the need for this project came from the practice of designing and implementing the VHAAC environment by a multidisciplinary analytics team. The main ADR design artefact in this project – a knowledge sharing method – was 'theory-ingrained' (Principle 2), because its design was guided by the theory of BOs (Carlile, 2004) and informed by the theoretical concept of secondary design (i.e. design-in-use) (Germonprez et al., 2011), as described in the next section. The Build, Intervene and Evaluate (BIE) phases of our ADR project were fully intertwined, with the emerging method shaping and being shaped through its use (Principle 3 of ADR), as described in the subsequent sections. The roles of VA experts and domain experts were mutually influencing (Principle 4 of ADR). We were also building the method while evaluating it in the authentic practice (Principle 5 of ADR). Throughout to the project, ADR-related research data were collected using two methods. The first method included an ongoing collective reflection-in-action (Levina, 2005) by the ADR team members, during each ADR cycle. The second method of data collection included observations of the effects of the actual intervention (Principle 5 of ADR), assessed by the domain experts' improved ability to transform their practice (Carlile, 2004) through VA. The main design artefact gradually emerged and was shaped by its use in the real-life context (Principle 6). The proposed method was then observed as an instance of a class of problem that was sharing of knowledge from VA experts and domain experts in multidisciplinary VA teams (Principle 7). Formalization of learning included design knowledge in the form of the proposed knowledge sharing method and an initial set of design principles. The following section introduces the theoretical foundations, also known in ADR as kernel theories (Sein et al. 2011), which informed our design. Further details of our ADR project implementation are described in the subsequent sections.

5 Theoretical Foundations (ADR kernel theories)

5.1 Theory of Boundary Objects

We recognize the research problem of knowledge sharing from VA experts to domain experts as the theoretical problem of boundary spanning (Lave & Wenger, 1991) across disciplinary knowledge boundaries (Carlile, 2002). The term boundary object (BO) was initially introduced by Star and Griesemer (1989) to describe an artefact/concept/object that serves as a translating device across knowledge boundaries of different kind. As such BOs could facilitate development of shared meaning across intersecting communities of practices (Bowker & Star, 1994) as well as facilitate knowledge sharing and mutual learning in a multi-contextual and a multi-perspective setting (Carlile, 2002). In our research we adopt Carlile's (2002, 2004) integrative framework for managing knowledge across boundaries, which conceptualizes three different types of BOs: syntactic, semantic and pragmatic. They are briefly described as follows:

Syntactic boundary objects establish a common lexicon for individuals to represent and share their knowledge. As such, they enable *transfer of knowledge* across an *information-process* boundary. Examples include simple charts, standard reports, or informal drawings of concepts. Individuals involved in sharing of syntactic BOs are assumed to have a sufficient common knowledge to *directly* interpret BO in their own disciplinary context, without any negotiation of meaning. However, when novelty arises, transfer of knowledge based on information-processing approach becomes problematic and syntactic BOs are no longer sufficient.

Semantic boundary objects enable *translation of knowledge* across an *interpretive* (i.e. semantic) boundary. This boundary occurs when a shared meaning cannot be achieved due to ambiguity and interpretive differences in understanding of the shared BOs. Semantic BOs thus enable co-creation of shared meaning and understanding by engaging disciplinary communities in a dialogue and negotiation. When using semantic BOs, individuals from different communities also change and adapt their domain-specific knowledge in order to reach a shared understanding (Brown & Duguid, 1991; Wenger, 1998). Examples of semantic BOs are metaphors and stories.

Pragmatic boundary objects facilitate a more complex process whereby individuals on different side of a knowledge boundary *transform* their individual disciplinary knowledge. The need to transition from a semantic to pragmatic boundary occurs when the novelty of semantic BOs results in different interests that need to be negotiated and resolved. Working at pragmatic boundaries is challenging as it involves dealing with different and often conflicting interests, organizational politics, disciplinary norms and 'creative abrasions' (Leonard-Barton & Swap, 1999). Resolving these challenges at the pragmatic boundary results in individuals developing both the common knowledge as well as their respective domain-specific *knowing-in-practice*. This in turn, enables individuals to apply the newly acquired domain-specific knowledge in their own context in order to tackle novel disciplinary problems and innovate on their own. Examples of pragmatic BOs include various trade-off methodologies used by multidisciplinary teams as they provide opportunities to recognize domain knowledge embedded in disciplinary practice, negotiate interests, advance shared knowledge, all while transforming domain knowledge of all participants.

Carlile (2004) suggests that different types of BOs could be used to span knowledge boundaries in different ways. Also, some BOs may be more suitable than others for a particular boundaries. Moreover, BOs are often combined and their interaction enables spanning of different types of knowledge at the particular boundary.

The main knowledge boundary in our project was found between VA experts and domain experts with expertise in cooperative enterprises. They formed a multidisciplinary team in order to co-design and implement the first-of-its kind industry-wide visual data exploration environment. Either group of experts could not do it on their own, as their respective domain expertise was not sufficient. The complex nature of our research problem thus required both groups to work at syntactic, semantic and pragmatic multidisciplinary knowledge boundaries. The theory of BOs by Carlile (2004) was therefore suitable as a kernel theory (Sein et al., 2011) for our ADR project.

5.2 The Concept of Secondary Design

The second theoretical perspective relevant for our research come from the previous theorization of the so-called secondary design in design science research (Germonprez & Hovorka, 2011; Germonprez et al., 2011; Lakew & Aryal, 2015). While in the traditional design and implementation of IT applications, including DVs, the role of intended users is often reduced to that of a source of design requirements (Germonprez et al., 2011), this is rapidly changing. The new types of IT systems make it "impossible for a primary design effort to completely specify all possible system uses ex ante" (Germonprez et al., 2009, p.4).

In response, a growing community of researchers turned their attention to "design-in-use", also known as secondary design. As Lakew and Aryal (2015) explain "[s]econdary design is a process by which users define the role of technology features in their daily practices" (p.1). Consequently, "secondary design recognizes that practice is not the result of design but rather a response to it" (Germonprez et al., 2011, p.663).

The concept of 'secondary design' is highly relevant for a new class of information systems that continue to grow and constantly change-in-use, but *without* any intervention of the initial designers. These "systems undergo an initial, primary design process where features are built in prior to general release. Following implementation, people engage in a secondary design process where functions and content emerge during interaction, modification, and embodiment of the system in use." (Germonprez et al., 2011, p.665). Examples of these constantly-evolving systems include social-media systems (Germonprez et al., 2011), digital platforms (Montealegre et al., 2014), learning management systems (Lakew & Aryal, 2015), and we argue, interactive visual data exploration environments as defined in this project.

Particularly relevant for our research are different aspects of knowledge and knowledge sharing involved in primary and secondary design. Germonprez et al. (2011) observe that primary design depends on the user knowledge harnessed and transferred to the primary designers during design requirement elicitation. Secondary design, on the other hand, focuses on users' actual experiences of using technology in their own practices, that is '*design-in-use*', which in based on their knowing-in-practice (Orlikowski, 2002). Consequently, secondary design shifts the focus from designing an artefact to solve a particular problem, with the requirements elicited from the intended users of this artefact, to *enabling* the secondary designers to solve their own contextualized problems (Germonprez et al., 2011). Secondary design thus "becomes interactive use and not mechanistic problem solving and recognizes the innovative tinkering, tailoring, and reflection which users apply to workarounds and unforeseen solutions to the human's problems" (Germonprez et al., 2011, p.3).

So far, secondary design has been investigated by the design science research and human computer interface research communities. To the best of our knowledge, secondary design is yet to be investigated in the context of VA for non-technical decision makers. As VA tools are meant to facilitate exploration of problem by subject matter experts, rather than offer a solution to a pre-defined problem (Stodder, 2013; Thorp, 2013), we observe that these domain experts need to engage in secondary design.

Moreover, when visualization is conceptualised as a process rather than an outcome (Franks, 2013), design and implementation of a VA platform do not stop after the initial features are completed and evaluated by the intended users. Instead, when primary designers complete the initial design and implementation, the secondary designers continue to shape the platform through their own visual data exploration, in particular through their own thinking and problem solving. Therefore, to be useful, any VA platform needs be designed-in-use by its secondary rather than primary designers.

Using the concept of secondary design, we therefore frame our research problem as the problem of enabling domain experts to engage in secondary design (i.e. design-in-use) through visual data exploration, as they have the necessary subject matter expertise and contextual understanding of data being explored. We are interested how this could be achieved in the context of multidisciplinary teams, through *a deliberate method* of knowledge sharing from primary designers (VA experts) to secondary designers (domain experts), which ultimately enables secondary designers to use VA as a thinking tool rather than just focus on visual outputs. Based on Carlile (2004) we recognize that knowledge sharing from primary to secondary designers in VA occurs across different kinds of knowledge boundaries. In the following sections we describe how we implemented the project, starting from the main type of VA-related BOs which we used and designed to enable and facilitate knowledge sharing across disciplinary boundaries.

6 ADR Implementation: VA-related Boundary Objects for Knowledge Sharing from VA Experts to Domain Experts

This section describes different types of VA-related BOs we used to enable and facilitate VA-related knowledge sharing from the VA experts to domain experts in our project. Drawing from the ADR kernel theories, we recognize that any multidisciplinary collaboration involves a number of different boundary objects. In this research we focus only on VA-related boundary objects and their role in enabling the research team to work across- different kinds of knowledge boundaries. Also informed by the ADR kernel theories, we recognize VA experts as primary VA designers, and domain experts as secondary, here named "principal VA designers". This renaming was done to emphasise their principal value-adding role in using their domain expertise to make sense data through visual data exploration. The three main phases of knowledge sharing and the associated BOs are described as follows:

– ***Phase 1: Use of syntactic VA-related BOs to raise the awareness of domain experts (ADR Cycle 1)***

In the first phase we used two types of syntactic VA-related BOs, with the overall purpose to raise the awareness of the domain experts of the new opportunities created by VA tools, when applied to our growing data set. The first type of syntactic BOs consisted of a number of data visualizations (DVs), created by the primary designers using the VHAAC data exploration environment, which at the time was in early stages. These DVs were used to inform the domain experts about the initial findings from the data.

The second type of BOs included data-driven visual stories that were created by VA experts out of static DVs, which were combined to illustrate possible decision-making scenarios. These stories presented to the domain experts, in a step-by-step manner, using the provided story telling features of the software application (Tableau). Both data visualization and visual stories were based on the VA experts' understanding of decision-making needs of different intended users. In order to elicit these needs, the VA experts collected data through interviews with domain experts and design thinking activities.

Our use of static DVs as static boundary objects did result in new insights gained by the domain experts, both within the multidisciplinary team and the wider advisory group of industry practitioners. Presented in the visual form, the VA experts' findings from the VHAAC were immediately augmented with new insights by the domain experts who could place these findings in the relevant historical context and understand their importance.

However, very soon these syntactic BOs were found to be very limited. Thus, asking users (with no previous VA experience) to communicate their data-related decision-making and data exploration needs so that they could be "transferred" into DVs and visual stories was not found to be effective. This is because of the well-known problem of "not-knowing what you don't know", especially when experiencing something for the first time.

At the same time the VA experts had very limited understanding of the cooperatives' data. Apart from creating static DVs to answer experts' initial questions, their ability to create insightful DVs and data-driven visual stories was equally limited. After evaluating our shared experience, collectively, we reached the limit of knowledge transfer across the disciplinary boundary thus creating the need for new types of VA-related BOs.

– ***Phase 2: Use of semantic BOs to engage in transformative co-creation (ADR Cycle 2)***

In this phase the VA experts decided to look for another type of VA-related BOs to enable translation of knowledge across disciplinary boundaries, not just its transfer, as in Phase 1. First of all, we looked for other examples of public visual data exploration environments developed in other industry sectors, similar to what we intended the VHAAC to become. Guided by the theory of BOs, we needed to make sure that any chosen example came from the context that was understandable to both VA and domain experts. We found an example of a nation-wide, visual data interactive environment using open data on senior citizens in Australia. Although very simple, this exemplary environment was very effective. First used as a syntactic BO, this environment helped the VA experts to illustrate how static data visualization (i.e. visulisation as output) differed from interactive visual exploration (visualisaion as a process) in order to facilitate the shift in their mindset from DV to VA. The exemplary environment was also used to demonstrate basic features of a DV tool, as much as it allowed us.

However, throughout our collective exploration and discussion, the same exemplary environment became a semantic BO. This is because it initiated and enabled our '*collective future imagining*'. More precisely, through collaborative exploration of different options of the exemplary environment, the multidisciplinary team engaged in in future-oriented brainstorming guided by the questions such as: "How would this look like in the VHAAC environment"? "Can we imagine something similar in relation to cooperatives' data'? and so on. Yet, the knowledge barrier remained, thus creating the need to keep exploring different kinds of BOs.

Informed by the previous insights from the ADR kernel theory again, in particular a possibility of using storytelling and stories for knowledge translation, we turned our attention back to visual stories. However, rather than using a data-driven method whereby static DVs are sequenced in a visual story (as in Phase 1), we shifted our collective focus from *data* to interesting industry *problems and opportunities* related to the cooperatives. In other words, our previous approach of looking at data in order to see what could be discovered there, turned out to be limited for two reasons. First, it constrained our exploration of possibilities, because it was limited by 'what was there in data' as perceived by VA experts. Second, our disciplinary knowledge barrier remained as data-driven stories still focused on knowledge transfer. It is important to note that this data-driven approach (i.e. looking at data in order to find and visualise interesting insights) is often practiced in the DV projects, especially if they are led by analytics experts. We discovered these limitations through our ongoing collective reflection.

Consequently, we decided to 'avert our collective gaze from data' and instead focus on problems and questions posed by the domain experts. For example, domain experts wanted to know: "Why are cooperatives demutualized over time", "Why do cooperatives close down?" "What is the story of business cooperatives in Australia?" It is important to note that there were no pre-defined data attributes that could enable VA experts to search and visualize the existing data in order to answer these questions. Instead, these questions could be answered only through visual data exploration by domain experts, supported by VA experts. Consequently, we started using problem-driven visual stories as semantic BOs that in turn required very close collaboration between VA and domain experts. For example, domain experts would start to translate the problem into a number of scenarios and with VA experts proceeded to turn these into visual stories (as much as possible based on available data), while recording the limitations of the existing data sets. Whenever required, domain experts would engage in additional data collection, using for example, historical archives, databases of historical coops-related newspaper and other articles, further interviews and case studies. After collecting any new data, domain experts engaged in historical research, which was required to cross-reference, reconcile, validate and interpret the collected data in a particular historical context.

In this phase we also used a number of techniques that were designed to gradually turn domain experts, from VA users into *principal designers*. For example, primary designers (VA experts) started from a common practice of 'walking with' principal designers, first through visual representations towards interactive collaborative visual explorations, noting their comments. It is important to note that unlike the "traditional" user feedback sessions where the main objective would be to improve the main features of the user interface or application, our main objective here was *not* to improve what was essentially primary designers' re-construction of domain experts' stories. Similarly, the collected feedback was not used to capture and "reconstruct" subject matter experts' way of thinking and visualise it. Looking from the knowledge management (KM) this would be an equivalent of trying to capture and document somebody's tacit knowledge that according to prior KM research cannot be done effectively (Nonaka, 1994). Instead, the main objective was to facilitate the gradual process of '*becoming*' principal designers by helping them to tap into their own knowing-in-practice more and more.

– ***Phase 3: Use of pragmatic BOs to transform domain practice (ADR Cycle 3)***

The shift from Phase 2 to Phase 3 occurred when domain experts started using visual data exploration guided by their knowing-in-practice, which resulted in different types of transformation of their own practices. The key enabler of this transformation was the VHAAC environment that we recognized as a pragmatic boundary object, which was constantly-in-making. Through the process of collective reflection-in-action we observed the following types of transformation. First, through the use of the VHAAC environment, domain experts – now in the role of principal designers (still supported by VA experts on the need basis)—started transforming and expanding the existing body of knowledge about Australian cooperatives, both in industry and research literature. For example, they started challenging the common myths about cooperatives, such as why they dissolve and de-mutualize (Patmore et al., 2021).

The second type of transformation occurred when domain experts stated providing insights gained through visual data exploration to the wider cooperatives industry sector to support decision-making by different stakeholders, especially during crisis. For example, during the Australian bushfire disasters in Nov 2019, domain experts were able to provide historical insights about cooperatives' resilience and positive societal impact during similar natural disasters to the Australian Business Council of Cooperatives and Mutuals.

The third type of transformation occurred when the domain experts started to innovate on their own. For example, they invented a new practice of crowdsourcing of cooperatives-related data form other industry practitioners, using the form they designed for an easier upload into the VHAAC by the VA experts.

Our use of the pragmatic BO (the VHAAC) in Phase 3 also resulted in another shift of our collective VA-related mindset. While we started with the main focus was on VA technology features and data, in this phase we observed that principal designers started to explore and see their practice and domain knowledge '*through data*'. Consequently, both technology and data started to 'fade into background', thus becoming the means of VA-enabled transformation of their domain knowledge. This in turn impacted on the ongoing

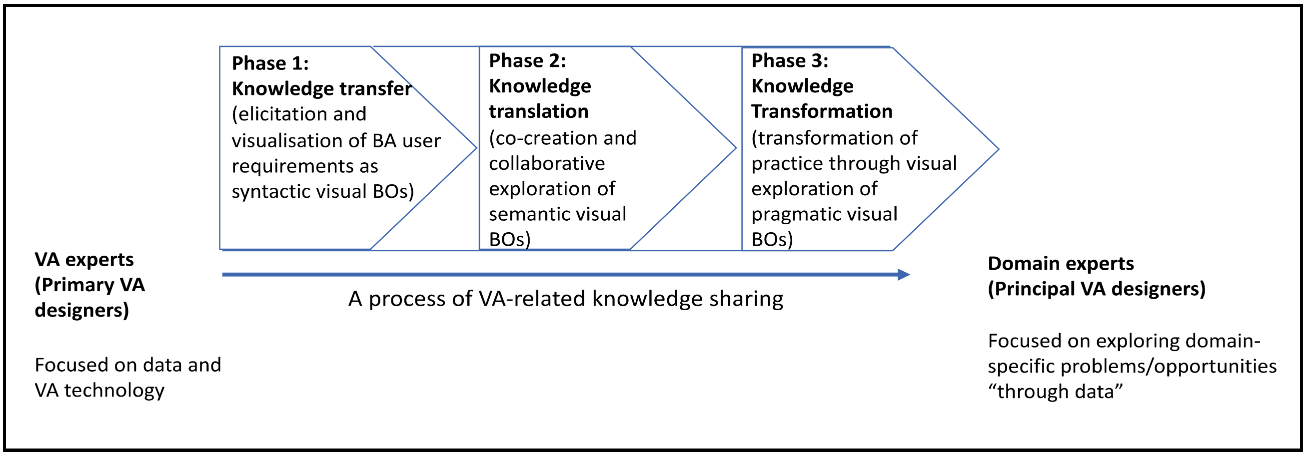

Fig. 2 A proposed method of VA-related knowledge sharing from VA experts for domain experts

design-use of the pragmatic BO that is the VHAAC environment as well as the domain experts' knowing-in-practice.

7 A Three-phase Method for Knowledge Sharing between VA Experts and Domain Experts (ADR design artifact)

In response to the stated research question, we theorize a three-phase method for a gradual transfer of knowledge from primary to principal VA designers, using VA-related syntactic, semantic and pragmatic boundary objects. The method draws from our collective insights from the project. We recognize the problem of knowledge sharing in the VHAAC project as an instance of a class of problems, which is is knowledge sharing in multidisciplinary VA teams among VA experts and non-technical domain experts.

The proposed method is depicted by Fig. 2. As shown the first phase focuses on a knowledge transfer achieved by transfer of syntactic BOs across knowledge boundaries in the form of static DVs and their combinations. The second stage includes knowledge translation through co-design of semantic BOs as well as the use of exemplary BOs for *collective future imagining*. The third phase involves knowledge transformation, which is focused on empowerment of domain experts to 'see through visual data' in order to transform their own and wider industry practice. Further details of each phase are summarized in Table 1, including examples of different types of VA-related boundary objects. It is important to point out that depicted phases were not defined upfront. Instead, they were emerging throughout ADR cycles.

Table 1 Different phases of VA-related knowledge sharing from primary to principal VA designers

	Phase 1: Knowledge Transfer	Phase 2: Knowledge Translation	Phase 3: Knowledge Transformation
Goals	Present and inform	Engage and translate	Transform
Focus	Data and features of VA technology demonstrated by primary designers	Domain-focused Problems and opportunities Identified by principal designers	Problem exploration by 'seeing through data'
Boundary objects used in each phase	Syntactic - Static data visualization - Data driven stories	Semantic: - Co-created problem-driven visual stories - External VA environments used to elicit 'pattern thinking'	Pragmatic: - Interactive VA environment used for problem-driven visual data exploration
Mode of knowledge sharing	Transfer from VA to domain experts	Translation across disciplinary boundaries	Transformation of both VA experts' and domain experts' disciplines through co-design
Led by	Primary designers (VA experts)	Critical shift in leadership from primary to principal designers	Principal designers (domain experts)

Therefore, building, implementation and evaluation of the main ADR design artifact (i.e. the proposed method) were highly intertwined.

8 Design Principles (ADR formalisation of design knowledge)

The following design principles capture design knowledge related to the proposed 3-phase method of VA-related knowledge sharing from primary to principal designers. They were derived through collective reflection-in-action (Levina, 2005) by the project team and refined throughout the ADR cycles.

DP1: The sequence of BA-related BOs matters

While developing the principal designers' ability to engage in a process of visual data exploration, we found that the actual sequence of boundary objects was important. For example, attempting to use visual stories as semantic or even pragmatic boundary objects immediately and without progressing through previous stages was not found to be very effective. Thus, creating awareness of data and technology through the use of syntactic BOs, followed by exploration of possibilities through 'collective future imagining' made possible by semantic BOs, enabled us to form the foundations of our shared knowledge. This in turn paved the way for co-creation of new semantic boundary objects, and later on our work at the pragmatic knowledge boundary.

DP2: Gradual co-creation of VA-related BOs should enable 'the critical shift' from primary to principal designers

When the initial static data visualizations were used as syntactic BOs, we observed that these BO were 'transferred' across knowledge boundaries. Using a metaphor, an ADM team member described this transfer as "tossing over the disciplinary wall". Similar transfer of BO also occurred when primary designers used design thinking to elicit data and decision-making requirements from the domain experts, in order to turn insights into data-driven visual stories. In both cases these BOs remained unchanged through transfer. While initially effective (in Phase 1), these BOs did not result in the transfer of knowledge that would empower domain experts to effectively engage in visual data exploration on their own.

On the other hand, problem-driven visual stories used as semantic Bos in Phase 2, were effective because they were co-created through a collaborative data exploration process. More importantly, this exploration process resulted in what we termed 'the critical shift' in a gradual transfer of VA knowledge. The shift occurred when the principal designers) took over the co-creation of visual stories from the primary designers.

DP3: When spanning semantic and pragmatic boundaties, it is important to use VA-related BOs that engage principal designers in 'thinking in patterns'

We found that BOs that engaged principal designers in 'pattern thinking' were very effective for knowledge translation and ultimately knowledge transformation. For example, the semantic BO we used in Phase 2 (a visual exploration environment from another industry sector), enabled secondary designers to 'see' new possibilities for the VHAAC environment by thinking in patterns. This way of thinking was stimulated by a deliberate practice of 'collaborative future imagining' implemented through brainstorming and guided by the questions designed to initiate pattern thinking. However, we found these BO to be effective only if the principal designers could relate to them either through their experience or common knowledge. For example, the VA environment related to aging was easy to use and understand due to our common knowledge. This in turn enabled more effective thinking in patterns by 'translating' the experience with this VA environment into imagined possibilities for VHAAC. We also observed the evidence of thinking in patterns in Phase 3, when the multidisciplinary ADR team came up with new ideas for the future VHAAC-like VA environments. An example is a future interactive shared VA environment for agricultural cooperatives to understand and negotiate ownership of their data.

DP4: Create opportunities for sharing of VA-related BOs between principal designers and other domain experts

We found that when the principal designers (i.e. domain experts) shared both semantic and pragmatic BOs with a wider group of industry practitioners, their learning to explore data became even more effective, and certainly more engaging. Even while these BOs were in the development stage. As these domain experts all have shared contextual knowledge, we found that the principal designers were able to share the experiential knowledge of "their own thinking process". The same type of experiential knowledge could not be easily shared with the primary designers due to boundries in disciplinary knowledge.

DP5: Empower domain experts to use VA as a thinking tool

We observed that syntactic BOs in the form of static data visualisations placed too much emphasis on 'seeing data' in a new visual form. While important, especially in Phase 1, we also found that this was limiting. We argue that the effective knowledge transfer occurs when the principal designers start to see their practice (i.e. problems-at-hand and future opportunities) 'through data'. When this happens, the VA environment such as VHAAC becomes a thinking tool. The use of such a tool is not pre-defined as in DV. Instead, it is guided by the domain expert's knowing-in-practice.

The proposed design principles are by no means exhaustive. As such, they are expected to be refined and extended through further research and use in other contexts.

9 Theoretical and Practical Contributions

This research offers several theoretical and practical contributions to the IS field, as follows. By focusing on VA for non-technical decision makers, we address an important research gap in the BA-related literature in IS, which remains focused on the mainstream analytics and to a much lesser extent, data visualization. The proposed method of knowledge transfer, translation and transformation from VA experts to domain experts also contributes to the growing body of IS research on organizational use of analytics (Abbasi et al., 2016; Vidgen et al., 2017). At the same time, our research opens an interesting research opportunity to investigate the proposed method as a potential mechanism for analytics value creation in an organization setting.

The proposed 3-phase method also addresses the previously observed research gap related to the transfer of knowledge from analytics to non-technical experts (Holzinger, 2016; Benbya, et al. 2021). Based on our research findings, we argue that knowledge sharing between VA experts and domain experts goes beyond VA-related knowledge transfer. As demonstrated in our research, this process also includes knowledge translation and ultimately, knowledge transformation, which empowers non-technical decision makers to transform their own practice, with VA becoming 'a thinking tool'. The proposed method also confirms the previous finding by Ghasemaghaei et al. (2018) about the importance of domain knowledge in BA. We extend this research to VA and emphasize the role of domain experts who are best positioned to make sense of visual data through interactive exploration, guided by their knowing-in-practice (Orlikowski, 2002).

Our proposed method also contributes to the KM literature on knowledge sharing processes, exemplified by (Alavi and Leinder, 2001; Nonaka, 1994), which we advance by exploring a VA-related knowledge sharing process in multidisciplinary teams at a very granular level and using VA-related boundary objects. In doing so we also contribute to the emerging stream of research, which focuses on the role of KM in BA, as discussed by Hota et al. (2015), Pauleen and Wang (2017), Tian (2017) and Marjanovic (2021).

Our research also explains why common data visualization practices, which are often limited to design and sharing of static data visualizations based on user requirements, are not sufficient when it comes to non-technical decision-makers developing their own ability for visual data exploration. These static DVs correspond to syntactic BOs, we used in Phase 1. The proposed method explains how to proceed beyond the initial phase using semantic and pragmatic boundary objects in order to empower domain experts to use VA as a *thinking tool*.

By situating our project in an industry-wide context, we also contribute to an important nstream of research on societal use of analytics (Gupta et al., 2018) as the new frontier of analytics research, in particular VA research. We argue that this is a important contribution as industry-wide projects of this complexity and duration, with the authors as co-leaders using the research outcomes to advance the practice of VA, are still rare in the IS literature. Also, given the societal importance of cooperatives (ICA, 2021a, 2021b), our project opens new opportunities for further IS research beyond VA in this important industry domain, which is yet to be explored by the IS community.

In terms of practical contributions, we offer a method that was developed, extensively evaluated and refined through use in our own ongoing large-scale VA project, now for more than six years. This is an important contribution, given the current industry trend of deploying multidisciplinary analytics teams.

The method goes beyond the common industry practice of developing visual dashboards, whereby data visualization experts work together with the user to elicit user requirements and (co-)create various visualisual outcomes (i.e. visual representation). We used this approach in Phase 1. Then in Phase 2 we observed that the visualisation process of 1) getting to know data, 2) creating visual explanations of data and 3) framing and visualisation of stories, which is often used in practice, is entirely *data driven*. We then recognised the need to 'avert our collective gaze from data' which was an important shift in our VA mindets. This led us to Phase 3 in which we focused on developing non-technical domain expert's ability to use VA as a thinking tool, guided by their knowing-in-practice (Orlikowski, 2002).

The proposed method could be adopted and refined by other multidisciplinary teams in different contexts beyond cooperatives. In particular, it is suitable for other industry-wide interactive visual data exploration environments, which are accessed by a diverse group of stakeholdersts with different decision-making needs that cannot be articulated in advance. Examples include future VHAAC-like environments in aged care or education sectors. We acknowledge that the nature of data in these environments would be different, as well as data collection methods that in our project included historical data. However, the challenge of knowledge sharing across disciplinary boundaries would be present, thus making our proposed method applicable to these settings.

Inspired by prior call for future IS research to address COVID-19 challenges by Chang et al. (2021), we could also envisage a future industry or society-wide environment for visual exploration of COVID-19-related data by different stakeholders with diverse domain experitise. Our proposed method for knowledge transfer, translation and transformation would be very relevant in the envisaged environments, given the stakeholders' very diverse domain expertise coupled with the need for rapid knowing-in-practice, which is both used and developed through visual data exploration by the domain experts themselves.

Finally, our research calls for a different kind of VA training for domain experts. Instead of being a source of "user requirements" for design of visual dashborads, we argue for their knowing-in-practice to be recognised as the most important for VA value creation. We thus envisage the proposed method to be used as an ongoing method of organisational learning through VA, instead of a short-term VA-focused skill-based training.

10 Conclusions, Limitations and Future Work

This paper described an innovative Action Design Research (ADR) project focused on the practice-formed research challenge of knowledge sharing between VA experts and domain experts working in the same multidisciplinary VA team.

To answer the research question: *How to effectively facilitate sharing of VA-related knowledge between VA experts and non-technical domain experts in multidisciplinary VA teams?* we proposed a three-phase method of knowledge transfer, transformation and translation through the use of different kinds of VA-related boundary objects among primary designers (VA experts) and principal designers (domain experts). The proposed method is founded in prior research from the fields of knowledge management (i.e. knowledge sharing), organization science (i.e. spanning of knowledge boundaries through boundary objects) and design science research (i.e. secondary design). We found that effective VA boundary objects need to be co-created rather than transferred across disciplinary boundaries. They also need to be used in a particular order to ensure effective transfer of different types of knowledge among primary and principal designers. VA-related BOs that stimulate 'thinking in patterns' were found to be effective in spanning semantic and pragmatic knowledge boundaries. Most importantly, knowledge transfer from VA experts and domain is best facilitated through design-in-use and by learning to shift the focus from 'seeing data' to 'seeing through data',

The proposed knowledge sharing method and the articulated design principles have important consequences for education and training of non-technical decision-makers in using VA for visual data exploration rather than just static data visualization. Therefore, workplace training and classroom learning, where the main emphasis is on skill-based training and technical features of a data visualization platform, is less likely to develop practitioner's ability to use visual data exploration as a thinking tool. Rather than going through training manuals, which we observed to be the main mode of training in many workplaces, it is important to engage practitioners in a gradual process, first through the use of syntactic boundary objects (developed by VA experts), semantic boundary objects co-created through knowledge sharing and then gradually shaped into pragmatic boundary objects through design-in-use.

Our research project has several limitations. It was conducted in a specific context (Australian Co-operatives). The ADR team also conducted this research in their own practice, as researchers/practitioners who were committed to collaboration and knowledge sharing. We acknowledge that this may not always be the case, as different yet-to-be explored barriers may exist in different organizational settings. For example, VA experts external to the organization, may face trust or some other contextual issues when working with subject-matter experts for the first time. We also recognize that different multidisciplinary teams experience different team dynamics, which in turn may impact on the process of knowledge transfer. Therefore, further research is required to understand how the proposed method would work in other organizational contexts and different types of multidisciplinary VA teams (e.g. self-selected or put together). We also did not investigate the issue of knowledge retention. Given the onoing nature of our project, which is still in progress, we see knowledge retention as an important future direction of our research after the completion of the current project.

As the project continues, our project team, now led by the domain experts, continues to discover new possibilities for future VHAAC-like, VA projects in other domains. In order to set the foundations for these projects, our current and future research include design and implementation of innovative learning methods for both VA experts and non-technical VA users (i.e. 'principal designers') in industry and university settings.

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Declarations

Conflict of Interest None.

References

Abbasi, A., Sarker, S., & Chiang, R. H. (2016). Big data research in information systems: Toward an inclusive research agenda. *Journal of the Association for Information Systems, 17*(2), i–xxxii.

Alavi, M., & Leidner, D. E. (2001). Review: Knowledge management and knowledge management systems: Conceptual foundations and research issues. *Management Information Systems Quarterly, 25*(1), 107–136.

Andrienko, G., Andrienko, N., Drucker, S., Fekete, J-D., Fisher, D., et al. (2020). Big data visualization and analytics: Future research challenges and emerging applications. *BigVis 2020 - 3rd International Workshop on Big Data Visual Exploration and Analytics*, Mar, Copenhagen, Denmark.

Australian Institute (2012). *Who Knew Australians Were so Co-operative? The Size and Scope of Mutually Owned Co-ops in Australia,* Australian Institute, Bruce: ACT.

Australian Senate. (2017). *Australian Government response to the Senate Economics Reference Committee Repor*t, Australian Government, Available from: https://www.aph.gov.au/Parliamentary_Business/Committees/Senate/Economics/Cooperatives/Government_Response. Accessed 29 Sept 2021.

Baker, J., Burkman, J., & Jones, D. R. (2009). Using visual representations of data to enhance sensemaking in data exploration tasks. *Journal of Association of Information Systems, 10*(7), 533–559.

Balnave, N., & Patmore, G. (2012). Rochdale consumer co-operatives in Australia: Decline and survival. *Business History, 54*(6), 986–1003.

Baskarada, S., & Koronios, A. (2017). Unicorn data scientist: The rarest of breeds. *Program, 51*(1), 65–74.

Baskerville, R. L., & Wood-Harper, A. T. (1998). Diversity in information systems action research methods. *European Journal of Information Systems, 7*, 90–107.

Baumeister, F., Barbosa, M. W., & Gomes, R. R. (2020). What is required to be a data scientist? Analyzing job descriptions with centering resonance analysis. *International Journal of Human Capital and Information Technology Professionals, 11*(4), 21–40.

BCCM. (2013). *About Cooperatives.* Business Council of Cooperatives and Mutuals. Available from: https://bccm.coop/what-is-a-co-operative/about-co-operatives/. Accessed 2 July 2022.

BCCM. (2019). *Blueprint for an enterprising nation.* Business Council of Co-operatives and Mutuals. Available from: https://bccm.coop/wp/wp-content/uploads/2019/04/2018-Blueprint-for-an-enterprising-nation.pdf. Accessed 2 July 2022.

BCCM. (2021). *The 2021 National Mutual Economy Report.* Business Council of Cooperatives and Mutuals. Available from: https://bccm.coop/wp/wp-content/uploads/2021/06/BCCM-2021-NME-Report.pdf. Accessed 2 July 2022.

Benbya, H., Pachidi, S., & Jarvenpaa, S. (2021). Special issue editorial: Artificial intelligence in organizations: Implications for information systems research. *Journal of the Association of Information Systems, 22*(2), Article 10. https://doi.org/10.17705/1jais.00662

Berinato, S. (2013a). *Your business needs insight, not just pretty picture*. Harvard Business Review. March, 19: 1–3. Available from: https://hbr.org/2013a/03/your-business-needs-insight-no. Accessed 2 July 2022.

Berinato S. (2013b). *Visualizing Data*, *HBR Insight Center Report.* Harvard Business Review Publishing. Available from: https://www.sas.com/content/dam/SAS/bp_de/doc/whitepaper1/ba-wp-hbr-visualizing-data-2276366.pdf. Accessed 2 July 2022.

Berinato, S. (2016). *Visualizations that really work*. Harvard Business Review.

Billiet A., Dufays F., Friedel S., & Staessens, M. (2021). The resilience of the cooperative model: How do cooperatives deal with the COVID-19 crisis? *Strategic change: Briefings in Entrepreneurial Finance*. First published: 10 March 2021. https://doi.org/10.1002/jsc.2393

Birchall, J. (2012). The comparative advantages of member-owned businesses. *Review of Social Economy, 70*(3), 263–294. https://www.jstor.org/stable/23257800. Accessed 2 July 2022.

Birchall, J., & Ketilson, L. H. (2009). *Resilience of the Cooperative Business Model in Times of Crisis, Sustainable Enterprise Programme*. International Labour Organization, Geneva: ILO. Available from: https://www.ilo.org/wcmsp5/groups/public/---ed_emp/---emp_ent/documents/publication/wcms_108416.pdf. Accessed 2 July 2022.

Bowker, G., & Star, S. L. (1994). Knowledge and information in international information management: Problems of classification and coding. In L. Bud-Frierman (Ed.), *Information Acumen: The Understanding and Use of Knowledge in Modern Business* (pp. 187–213). Routledge.

Brown, J., & Duguid, P. (1991). Organizational learning and communities of practice: Toward a unified view of working, learning, and innovation. *Organizational Science, 2*(1), 40–57.

Camm, J. D., Fry, M. J., & Shaffer, J. (2017). A Practitioner's guide to best practices in data visualization. *INFORMS Journal on Applied Analytics, 47*(6), 473–488.

Carlile, P. R. (2002). A pragmatic view of knowledge and boundaries: Boundary objects in new product development. *Organization Science, 13*(4), 442–455.

Carlile, P. R. (2004). Transferring, translating, and transforming: An integrative framework for managing knowledge across boundaries. *Organization Science, 15*, 555–568.

Chang, V., Goble, C., Ramachandran, M., Lazarus Jegatha, D., & Behringer, R. (2021). Editorial on mashine learning, AI and big data methods and findings from COVID-19. *Information Systems Frontiers, 23*, 1363–1367. https://doi.org/10.1007/s10796-021-10216-7

Chen, H. Chiang, R. H. L., & Storey, V. C. (2012). Business intelligence and analytics: From big data to big impact. *MIS Quarterly, 36*(4), 1165–1188.

Cole, R., Rossi, M., Purao, S., & Sein, M. (2005). Being proactive: where action research meets design research, in *Proceedings of the International Conference on Information Systems (ICIS-2005),* AIS, 325–336.

Cooper, K., Green T., & Tregilgas, P. (2013). *Co-operatives in Australia: A Manual*, Co-operatives Federation of NSW and RDA Mid-North Coast Inc.

Davenport, T. (2020). Beyond unicorns: educating, classifying and certifying business data scientists", *Harvard Data Science Review*, 2(2). https://doi.org/10.1162/99608f92.55546b4a

Dilla, W. N., & Raschke, R. L. (2015). Data visualization for fraud detection: Practice implications and a call for future research. *International Journal of Accounting Information Systems, 16*, 1–22.

Dilla, W. N., Janvrin, D. N., & Raschke, R. L. (2010). *Interactive Data Visualization: A New Directions*, Enlighten (2nd ed.). Analytics Press.

EURICSE-ICA. (2020). *The World Cooperative Monitor: Exploring the cooperative economy*. International Cooperatives Alliance. Available at: https://monitor.coop/en/media/library/research-and-reviews/world-cooperative-monitor-2020. Accessed 2 July 2022.

Few, S. (2006). *Information dashboard design: The effective visual communication of data*. O'Reilly Media.

Few, S. (2012). Show me the numbers: Designing tables and graphs for accounting information systems research. *Journal of Information Systems, 24*(2), 137–153.

Franks, B. (2013). *The value of a good visual, visualizing data: A harvard business review insight center report*. Harvard Business Publishing.

Freeze, R. (2018). Analytics in the pursuit of knowledge: Adapting the knowledge pyramid, Proc. of the 51st HICSS conference. Hawaii, USA.

Gatto, M. A. C. (2015). *Report: Making Research Useful: Current Challenges and Good Practices in Data Visualisation*. University of Oxford.

Germonprez, M., & Hovorka, D. (2011). Secondary design: A case of community participation, *Proc. of the Seventeenth Americas Conference on Information Systems*, Paper 212, Detroit, Michigan.

Germonprez, M., Hovorka, D., & Gal, U. (2009). Theorizing on secondary design. *Proceedings of JAIS Theory Development Workshop, Sprouts: Working Papers on Information Systems, 9*(41). Available from: http://sprouts.aisnet.org/9-41. Accessed 2 July 2022.

Germonprez, M., Hovorka, D., & Gal, U. (2011). Secondary design: A case of behavioural design science research. *Journal of the Association of Information Systems, 12*(10), 662–683.

Ghasemaghaei, M., Ebrahimi, S., & Hassanein, K. (2018). Data analytics competency for improving firm decision making performance. *The Journal of Strategic Information Systems, 27*(1), 101–113. https://doi.org/10.1016/j.jsis.2017.10.001

Gupta, A., Deokar, A., Iyer, L., et al. (2018). Big data & analytics for societal impact: Recent research and trends. *Information Systems Frontiers, 20*, 185–194. https://doi.org/10.1007/s10796-018-9846-7

Gurdal, E., Gul, T., Mete, S., & Mustafa, M. (2017). New knowledge in strategic management through visually mining semantic networks. *Information Systems Frontiers, 19*(1), 165–185. https://doi.org/10.1007/s10796-015-9591-0

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

Hill, R. L., Kennedy, H., & Gerrard, Y. (2016). Visualizing junk: Big data visualizations and the need for feminist data studies. *Journal of Communication Inquiry, 40*(4), 331–350.

Hiltbrand, T. (2021). Developing a new generation of Pi-shaped human resources. *Journal of Business Intelligence, 26*(1), 15–26.

Hindle, G., Kunc, M., Mortensen, M., Oztekin, A., & Vidgen, R. (2020). Business analytics: Defining the field and identifying a research agenda. *European Journal of Operational Research, 281*, 483–490.

Hohman, F., Kahng, M., Pienta, R., & Chau, D. H. (2019). Visual analytics in deep learning: An interrogative survey for the next frontiers,". *IEEE Transactions on Visualization and Computer Graphics, 25*(8), 2674–2693. https://doi.org/10.1109/TVCG.2018.2843369

Holzinger, A. (2016). Interactive machine learning for health informatics: When do we need the human-in-the-loop?", *Brain Informatics*, 3(2). https://doi.org/10.1177/0196859916666041

Hota, C., Upadhyaya, S., & Al-Karaki, J. N. (2015). Advances in secure knowledge management in the big data era. *Information Systems Frontiers, 17*, 983–986. https://doi.org/10.1007/s10796-015-9593-y

Huber, T. C., Krishnaraj, A., Monaghan, D., et al. (2018). Developing an interactive data visualization tool to assess the impact of decision support on clinical operations. *Journal of Digital Imaging, 31*, 640–645.

ICA. (2021a). *International Day of Cooperatives Press Release: Rebuild better together*. International Cooperative Alliance, 3 July 2021, Available from: https://www.ica.coop/en/media/library/press-releases/rebuild-better-together-cooperative-enterprises-can-lead-people. Accessed 2 July 2022.

ICA. (2021b). *World Cooperative Monitor 2021 Covid-19 Preview: Large Cooperatives at the Forefront of the recovery*. International Cooperatives Alliance, Available from: https://monitor.coop/sites/default/files/basic-page-attachments/wcm-covid-preview-1573522133.pdf. Accessed 2 July 2022.

Keim, D. A., et al. (2008). Visual analytics: Definition, process and challenges, In: Kerren A., Stasko J.T., Fekete JD., North C. (eds) Information Visualization. Lecture Notes in Computer Science, vol 4950. Springer, Berlin, Heidelberg. https://doi.org/10.1007/978-3-540-70956-5_7

Kosara, R., & Mackinlay, J. (2013). *Storytelling: The Next Step for Visualization*. Available from: http://kosara.net/papers/2013/Kosara_Computer_2013.pdf. Accessed 2 July 2022.

Lakew, N., & Aryal, A. (2015). Secondary design – as a supplementary knowledge base for HCI design, *Proc. of the Twenty-first American Conference on Information Systems*, Puerto Rico.

LaValle, S., Hopkins, M., Lesser, E., Schockley, R., & Kruschwitz, N. (2010). Analytics: The new path to value: How the smartest organizations are embedding analytics to transform insights into action, *IBM Institute for Business value,* IBM Global Business Services, 1–21, Available from: http://www935.ibm.com/services/us/gbs/thoughtleadership/ibv-embedding-analytics.html. Accessed 2 July 2022.

Lave, J., & Wenger, E. (1991). *Situated learning: Legitimate peripheral participation*. Cambridge University Press.

Leonard-Barton, D., & Swap, W. C. (1999). *When sparks fly*. Harvard Business Press.

Levina, N. (2005). Collaborating on multiparty information systems development projects: A collective reflection-in-action view. *Information Systems Research, 16*(2), 109–130.

Malhotra, Y. (2004). Why knowledge management systems fail? Enablers and constraints of knowledge management in human enterprises. In M. Koenig & T. Srikantaiah (Eds.), *Knowledge Management Lessons learned: What Works and What Doesn't"* (pp. 87–112). Information Today Inc.

Marjanovic, O. (2016). Empowering business users to explore visual data through boundary objects and storytelling, *Proc. of the 49th Hawaii International Conference on Systems Sciences HICSS-49*, IEEE Xplore, https://doi.org/10.1109/HICSS.2016.624

Marjanovic, O. (2021). A novel mechanism for business analytics value creation: Improvement of knowledge-intensive business processes. *Journal of Knowledge Management*. https://doi.org/10.1108/JKM-09-2020-0669 Ahead-of-print.

Mohit, D. (2021). Resilient to crises: How cooperatives are adapting sustainably to overcome COVID-19-induced challenges. *International Journal of Rural Management*. Epub ahead of print March 15, 2021. https://doi.org/10.1177/0973005221991624

Montealegre, R., Hovorka, D., & Germonprez, M. (2014). A coevolutionary view of information services development: Lessons from the U.S. national oceanic and atmospheric administration. *Journal of the Association for Information Systems, 15*(9), 577–613. https://doi.org/10.17705/1jais.00372

Morison, M. (2021). *Australia's secret to success is worth billions says BCCM's National Mutual Economy Report.* Business Council of Cooperatives and Mutuals, 2 July. Available from: https://www.icmif.org/news_story/australias-secret-to-success-is-worth-billions-says-bccms-national-mutual-economy-report/. Accessed 2 July 2022.

Newell, S. (2014). Managing knowledge and managing knowledge work: What we know and what the future holds. *Journal of Information Technology, 29*, 1–17.

Nonaka, I. (1994). A dynamic theory of organizational knowledge creation. *Organization Science, 5*(1), 17–37.

Orlikowski, W. J. (2002). Knowing in practice: Enacting a collective capability in distributed organizing. *Organization Science, 13*(3), 249–273.

Patmore, G., & Balnave, N. (2018). *A Global History of Co-operative Business*. Routledge.

Patmore, G., Balnave, N., & Marjanovic, O. (2020). Visualising organisations over time and space: The Visual Atlas of Australian co-operatives. In R.D. Lansbury, A. Johnson & D. van den Broek (Eds.), *Contemporary Issues in Work and Organisations: Actors and Institutions* (pp.143–155). Routledge.

Patmore, G., Balnave, N., & Marjanovic, O. (2021). Resistance is not frutile: Co-operatives, demutualization, agriculture, and neoliberalism in Australia. *Business and Politics, 23*(4), 510–528.

Patmore, G., Balnave, N., & Marjanovic, O. (2022). Business co-operatives in Australia: "Unlikely soil for a co-operative movement". *Enterprise and Society*, Firstview, 1-25. https://doi.org/10.1017/eso/2021.27. Published online: 5 July 2021.

Pauleen, D. J., & Wang, W. Y. C. (2017). Does big data mean big knowledge? KM perspective on big data and analytics. *Journal of Knowledge Management, 21*(1), 1–6.

Perdana, A., Robb, A., & Rohde, F. (2018). Does visualization matter? The role of interactive data visualization to make sense of information, *Australasian Journal of Information Systems*, (22), https://doi.org/10.3127/ajis.v22i0.1681

Phillips-Wren, G., & McKniff, S. (2020). Overcoming resistance to big data and operational changes through interactive data visualization". *Big Data, 8*(6), 528–539.

Polanyi, M. (1966). *The tacit dimension*. Routledge & Kegan.

Roelants, B., Dovgan, D., Eum, H., & Terrasi, E. (2012). *The resilience of the co-operative model* CECOP-CICOPA. Available from: https://www.cicopa.coop/wp-content/uploads/2018/03/cooperatives_and_employment_a_global_report_en__web_21-10_1pag.pdf. Accessed 2 July 2022.

Sein, M. K., Henfridsson, O., et al. (2011). Action Design Research. *MIS Quarterly, 35*(1), 37–56.

Star, S. L., & Griesemer, J. R. (1989). Institutional ecology, "translations" and boundary objects: Amateurs and professionals in Berkeley's museum of vertebrate zoology. *Social Studies of Science, 19*(3), 387–420.

Stodder, D. (2013) Data visualization discovery for better business decisions, *Best Practices Report*. *Third Quarter,* TDWI.

Stodder, D. (2015). Making smarter decisions faster: Applying self-service business intelligence technologies to data-driven objectives, *TDWI Best Practices Report, Third Quarter,* TDWI.

Stodder, D. (2020). Faster Insights from Faster Data, *TDWI Best Practice Report*, Q1, 2020.

Stull-Lane, P. (2021). *Define analytics: The changing role of BI's favorite catch-all term.* TDWI White paper, 9.2.2021. Available from: https://tdwi.org/whitepapers/2019/06/bi-all-tableau-define-analytics-the-changing-role-of-bis-favorite-catch-all-term.aspx. Accessed 2 July 2022.

Swoyer, S. (2013). Investigative computing: The new frontier in BI", *TDWI Hot Topic*, TDWI.

Talagala, N. (2019). The full stack data scientist: Myth, unicorn, or new normal? *Forbes,* Sept 11. Available from: https://www.forbes.com/sites/cognitiveworld/2019/09/11/the-full-stack-data-scientist-myth-unicorn-or-new-normal/?sh=57f1f7e12c60. Accessed 2 July 2022.

The Australian Senate (2016). *Senate Inquiry: Cooperative, mutual and member-owned firms*. Economics References Committee, Commonwealth of Australia. Available from: https://www.aph.gov.au/Parliamentary_Business/Committees/Senate/Economics/Cooperatives/Report. Accessed 2 July 2022.

Thorp, J. (2013). Telling stories with visual data: A glimpse into the future of narrative, *Visualizing Data: A Harvard Business Review Insight Center Report*, Harvard Business Publishing, 2013.

Tian, C. (2017). Big data and knowledge management: A case of déjà vu or back to the future? *Journal of Knowledge Management, 21*(1), 113–131.

Toreini, P., Langner, M., Maedche, A., Morana, S., & Vogel, T. (2021). Designing attentive Information Dashboards", *Journal of the Association of Information Systems*, Epub ahead of print, accepted May 2021.

Tufte, E. R. (1983). *The visual display of quantitative information*. Graphics Press.

Vidgen, R., Shaw, S., & Grant, D. B. (2017). Management challenges in creating value from business analytics. *European Journal of Operational Research, 261*(2), 626–639.

Watson, H. J. (2017). Data visualization, data interpreters, and storytelling. *Journal of Business Intelligence, 22*(1), 5–10.

Wenger, E. (1998). *Communities of practice: Learning, meaning, and identity*. Cambridge University Press.

Yuan, J., Chen, C., Yang, W., et al. (2021). A survey of visual analytics techniques for machine learning. *Computational Visual Media, 7*, 3–36. https://doi.org/10.1007/s41095-020-0191-7

Zhang, V. (2019). Stop searching for that data scientist unicorn, *InfoWorld*, Aug 9. Available from: https://www.infoworld.com/article/3429185/stop-searching-for-that-data-science-unicorn.html. Accessed 2 July 2022.

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