VISUAL ANALYTICS IN ORGANIZATIONAL KNOWLEDGE CREATION: A CASE STUDY

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VISUAL ANALYTICS IN ORGANIZATIONAL KNOWLEDGE CREATION: A CASE STUDY

Research paper

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Abstract

The conversion between tacit and explicit knowledge remains an often-discussed and highly relevant topic in organizational knowledge creation. Although prior research addresses this process, it primarily focuses on the conversion between tacit and explicit knowledge through social processes. This work discusses theories of organizational knowledge creation in the light of sociotechnical systems, and specifically extends them to the interaction between individuals and visual analytics systems that afford analytical decision making based on interactive visualization and knowledge discovery mechanisms. Based on related work, we develop a theoretical framework to explain novel mechanism for knowledge creation afforded by visual analytics systems. We evaluate our framework with a case study with one of the leading organizations in the automotive industry. Over the course of the case study, we observe and analyze interactions between domain experts and a newly introduced visual analytics system. Through our case study findings, we reveal novel mechanisms of organizational knowledge creation and discuss their implications.

Keywords: Knowledge Management, Knowledge Creation, Knowledge Conversion, Visual Analytics, Human-Computer Interaction.
1 Introduction

Knowledge is a primary resource for achieving and maintaining a competitive advantage (Nonaka et al. 2000), leaving knowledge creation as an important task for companies. The process itself is challenging, as it requires accessing the knowledge individuals possess, where they are often not aware of their own tacit or explicit knowledge. Tacit knowledge is bound to the individual and difficult to communicate in contrast to explicit knowledge that can be readily accessed (Nonaka and Takeuchi 1995). Nonaka and Takeuchi (1995) describe knowledge creation as an iterative process in which knowledge is created through the conversion between tacit and explicit knowledge. In this regard, traditional information system technologies have been studied to great extent. However, the role of more recent technologies, specifically those based on artificial intelligence (AI), remain understudied in the context of knowledge creation and conversion (Sanzogni et al. 2017). Hence, we consider the effect of a specific type of systems, visual analytics (VA) systems, on knowledge creation and their affordances to support the conversion between tacit and explicit knowledge. The term affordances is used here to describe possible goal-oriented actions that emerge from the relationship between IT artifacts and specified groups of actors in specific contexts (Hutchby 2001; Vyas et al. 2003; Zammuto et al. 2007).

VA is a branch of information visualization focused on the interactive visualization of information. It encompasses various aspects of analytical tasks in decision-making, including the pre-processing of raw data, building models and deriving recommendations from them, as well as their visualization to facilitate the generation of new knowledge (Thomas and Cook 2005). VA systems draw upon methods and techniques from information visualization and AI to afford their users the ability to draw conclusions based on available data, models, and recommendations, and to facilitate sensemaking (Keim 2010). Providing these affordances, VA systems play a focal role in knowledge creation (Federico et al. 2017). Research on the intersection between VA and knowledge creation has recognized their relevance (Fayyad et al. 1996; Sacha et al. 2014; van Wijk 2005) but has paid little attention to the process of knowledge conversion, especially in collaborative settings that go beyond individual interactions with a VA system. We address this gap with the following research question:

“What novel mechanisms of organizational knowledge creation and conversion are afforded by visual analytics systems?”

In answering this question, we aim to extend the work of others who have explored aspects of knowledge creation in the context of VA (Keim et al. 2008; Sacha et al. 2014). We aim to achieve this goal by drawing on the work of Nonaka and Takeuchi (1995) on the process of knowledge creation and conversion. Based on related work, we derive a theoretical framework and evaluate it empirically through a case study of a company in the automotive industry. Following this research design, we want to understand and conceptualize the process of knowledge creation and conversion in the presence of a VA system that proactively augments decision-making and cognitive reasoning. Hence, our contributions are as follows: (1) a framework, explaining the process of organizational knowledge creation and conversion afforded by VA systems; and (2) provision of novel mechanisms for organizational knowledge creation afforded through VA.

2 Theoretical Background

The following are descriptions of well-established models for knowledge creation in the context of organizations and VA. First, we describe the processes of organizational knowledge creation in Section 2.1. Next, we give an overview of popular models of knowledge creation in VA in Section 2.2.

2.1 Organizational Knowledge Creation

According to the knowledge-based view, knowledge creation capabilities are a strategic asset that contribute to organizations by helping to improve organizational performance (Grant 1996). Nonaka and Takeuchi (1995) contributed to the area of knowledge creation with their theory of knowledge creation,
dividing knowledge into the two types: explicit knowledge that can be externalized easily, for example, in words and numbers; and tacit knowledge that is inherent to the individual. The latter often not recognized by the individual as knowledge but rather is expressed through action, commitment, and involvement, which renders it notoriously difficult to codify and externalize (Wang et al. 2009).

Nonaka and Takeuchi proposed their SECI model to conceptualize the process of knowledge creation and the conversion from one knowledge type to another. It comprises the processes of socialization (S), externalization (E), combination (C), and internalization (I). During interactions between individuals (socialization), tacit knowledge is converted through shared mental models. Resulting tacit knowledge is converted into explicit knowledge by codifying it (e.g., in the form of words; externalization). External sources of explicit knowledge can be combined into more systematic and comprehensive sets of explicit knowledge (combination). Further, explicit knowledge can be transformed into tacit knowledge by individuals, which is closely related to the concept of “learning by doing” (Nonaka et al. 2000; internalization). The sequential iteration of each process phase of the SECI model creates a spiral of new knowledge. To increase knowledge, a central task of organizations is to ensure knowledge creation and conversion. (Iyengar et al. 2015).

Prior research supports the notion that the use of IT is positively related to the collection, storage, and dissemination of knowledge in organizations (Argote and Miron-Spektor 2011; Iyengar et al. 2015; Kim et al. 2016; Kyriakou et al. 2017; Trantopoulos et al. 2017). This previous work, however, focuses on storing and sharing information (Kim et al. 2016; Kyriakou et al. 2017; Trantopoulos et al. 2017), neglecting the role of model-based reasoning or interactive data visualization in knowledge creation in collaborative contexts, as they are afforded by VA systems (Nobarany et al. 2012). We build on this prior research to include these additional dimensions and analyze their effects on knowledge creation between VA users and their broader environment.

2.2 Knowledge Creation through Visual Analytics

VA has been described as “the science of analytical reasoning facilitated by interactive visual interfaces” (Thomas and Cook 2005). By using methods from knowledge discovery in databases, statistics, and AI, VA systems provide a range of affordances to perform analyses. The systems suggest relevant insights and analytical interfaces to human users, who, in turn, review and revise the system’s output (Keim et al. 2008). VA is closely related to the discipline of business intelligence (BI). In BI, data are also gathered, analyzed, and transformed into information, which can then be converted into new information or knowledge (Shollo and Galliers 2016). While VA and BI overlap, they differ in important aspects. VA is concerned mostly with the representation of complex and often unstructured large data sets, for example, in the context of exploratory malware (Wagner et al. 2017) or speech (Sacha et al. 2018) analyses, and the design of resulting visualization interfaces. In turn, traditional BI tools are developed for gathering and storing small amounts structured data, for example, through relational databases (Shollo and Galliers 2016). Furthermore, the scope of BI is not about the design of specific interfaces for exploratory analyses, but comprises technologies and strategies for the collection and analysis of data to make better-informed decisions (Davenport 2010). VA includes large amounts of both structured and unstructured data and is concerned with specific implementations of systems for exploratory analyses, which is why our focus here is on VA rather than BI.

In VA, a variety of models exist that can be related to knowledge creation, such as the classical visualization pipeline (Card et al. 1999; Card and Mackinlay 1997), the process of knowledge discovery in databases (Fayyad et al. 1996), and the sensemaking loop (Pirolli and Card 2005). The models of van Wijk (2005), who focuses on the system perspective, and Sacha et al. (2014), who emphasize the human perspective, have been widely adopted and enhanced and thus stand out within the literature.

Van Wijk’s (2005) operational model of visualization identifies three spaces – the data, visualization and user spaces – to describe the context in which visualizations operate. Wang et al. (2009) extend van Wijk’s model by adding a knowledge base to the model, combining different sources of knowledge. They also include the SECI model described earlier. Although, Wang et al. (2009) consider the SECI
model, their goal lies in improving visualization systems. Our study goes beyond improving visualization systems and aims at discovering novel mechanisms for organizational knowledge creation through VA. For instance, we find that knowledge within organizations can be externalized in three categories: (1) Features: Measurable properties of observed phenomena in analyzed data instances (Bishop 2006), such as the maximum voltage of a battery cell (note that while the term features can also be used to refer to system functionalities, we use the term hereafter only in the context of model inputs); (2) Labels: The aggregation of complex information to annotate or label observed data instances, taking prior knowledge into account (Bernard et al. 2018), such as a battery cell that is overheated; and (3) Models: Models and rules that describe the behavior of the analyzed data (Green et al. 2009), such as the if-then statement “if the maximum voltage is very high, the possibility of an overheated battery cell increases.”

The VA process model of Keim et al. (2010), extended by Sacha et al. (2014), focuses on user operations, combining automated analysis methods with user interactions to gain knowledge. Here, users can choose to apply either automated or visual analysis methods. When using an automated method, data mining techniques are applied to create models that fit original data and reveal interesting properties of the data set. These models are then used to evaluate and improve the visualization. If the user chooses to conduct a visual analysis, raw data are mapped directly to specific types of visualizations. Sacha et al. (2014) extend the original Keim et al. (2010) model by describing the process of knowledge creation through the interaction of the user with a VA system. Figure 1 depicts the Sacha et al. (2014) model: the gray boxes indicate the original model and the white boxes are our extensions. Here, the frequent interaction with the system leads to findings. Findings can either result in actions, if they are taken as input for additional system interactions, or insights, if they are interpreted based on previous domain knowledge. Insights can lead to hypotheses, which must be properly tested. To verify a hypothesis, a new interaction with the system is triggered by an action.

All the models mentioned describe knowledge creation through the interaction between a human and a VA system, with Wang et al. (2009) even explicitly incorporating the SECI model. Nevertheless, all these models focus on the interaction between a single user and the VA system. We propose that the interaction between humans and machines creates novel mechanisms for organizational knowledge creation (Iyengar et al. 2015). We build on the findings of the studies reviewed here and relate knowledge creation in VA to organizational knowledge creation to derive new, generally applicable mechanisms of knowledge creation afforded through VA.

3 Combining Organizational Knowledge Creation with VA

Both in the context of organizational knowledge management and visual analytics two well-known models, which are the SECI model (Section 2.1) from Nonaka and Takeuchi (1995) and the process of knowledge creation in VA Section 2.2 from Sacha et al. 2014, have been introduced. However, none of the two presented models alone serves to describe the process of organizational knowledge creation and conversion in light of collaborative settings, where more recent technologies, such as VA systems play a focal role (Sanzogni et al. 2017). We propose that novel mechanism for organizational knowledge creation can be explained by combing both the models from Nonaka and Takeuchi (1995) and Sacha et al. (2014).

Since the model of Sacha et al. (2014) focuses primarily on actions performed by the user, we consider it to be the most appropriate model for describing emerging mechanisms for organizational knowledge creation afforded through VA. In turn, the SECI model of Nonaka and Takeuchi (1995) serves well to describe knowledge creation in an organizational context, which emerges above all from the collaboration of individuals.

To build a theoretical framework, which serves to describe novel mechanism afforded through VA systems, we rearranged the existing components from the process of knowledge creation in VA and the SECI model. In the case of the process of knowledge creation in VA, we extend the model to account not only for the process of knowledge creation through direct interactions between users and the system, but also for indirect processes enabled by these interactions that affect knowledge creation within a
broader organizational context. To do so, we use the SECI model, where we connect each of the four phases to the model of Sacha et al. (2014).

Our result, shown in Figure 1, can be summarized as follows: During frequent interactions with the system, the mental model of the user is adapted continuously in externalization and internalization, both resulting in an augmentation of the system and the user. Tacit knowledge is externalized via the preparation of data, the training of models or the manipulations of the visualization (Section 3.1.2). In turn, explicit knowledge is internalized via the inspection of the data, the verification of the model, or the observations of the visualization (Section 3.1.4). While using the system, users can consult colleagues within the organization or share insights with them. This results in new socialization cycles triggered via a system interaction (Section 3.1.1). A user’s analysis can also result in the reconfiguration and combination of different data instances. This combination results from an action the user executes, but is performed by the system by connecting new data instances with each other and providing them to the user through visualizations (Section 3.1.3).

Figure 1: Conversion between tacit and explicit knowledge in VA. Gray boxes indicate components from Sacha et al. (2014), where we also use the SECI phases from Nonaka and Takeuchi (1995).

3.1.1 Socialization

Sanzogni et al. (2017) argue that systems cannot socialize with humans. Thomas and Cook (2005), however, propose that proper visualizations may lead to analytical discourse and the collaboration between system users from system interactions. Thus, even though a user cannot socialize with a system per se, an interaction with the system may trigger socialization with other individuals. Interactions can occur not only between system users, as mentioned by Wang et al. (2009) and Arias-Hernandez et al. (2011) but also with other individuals, such as colleagues from different departments or even outside an organization. For example, a finding as a result of a system interaction (Figure 1 - Socialization), may lead to the inherent wish of a user to consult another individual to validate an assumption. During these interactions, tacit knowledge is transformed through the exchange of metaphors or the adaption of mental models (Nonaka and Takeuchi 1995).

3.1.2 Externalization

Tacit knowledge can be externalized via features, models, or labels during an interaction between humans and machines (Bernard et al. 2018). Externalization in VA systems occurs in a process leading from the user towards the system. Based on context relevant knowledge, the user can interact with the VA system through manipulation, training, or preparation (Figure 1 - Externalization).
Knowledge creation through visual analytics

Manipulation: As a result of a previously defined goal, manipulations of a visualization can be triggered by user actions (Sacha et al. 2014). Even though the manipulation may not directly result in the augmentation of the system, it may contribute to the generation of new conscious and unconscious findings, which can later be used to train and thereby augment the system (Jackle et al. 2016). Since the visualization is influenced by the recommendations of the underlying model, the model has an indirect effect on actions performed by the user to complete a manipulation task (Green et al. 2009).

Training: After frequent manipulations, a user’s understanding of the system can evolve to the extent of being able to train the system consciously. This can happen through the provision either of features or labels. A feature serves as an input for models (Dor and Reich 2012). In the analysis of high-dimensional data sets in particular, expert knowledge about the data is required to select the right features (Thalmann et al. 2018). When users provide labels, they can be employed in combination with features to train a model. The model then interprets defined input features and classifies data according to the patterns derived from the labeled data set with the same features.

Preparation: To improve the system, the user can directly adapt its underlying data representation via data preparation. Here, the data can be prepared via transformations and processing to select features that represent the data (Amershi et al. 2014). The features can be used later as input data for the model, to adapt the visualization, or be stored within an organizational database available to other users.

In addition to externalization as a result of an action, Ragan et al. (2016) summarize different types of provenance during the process of VA. These serve well to externalize knowledge considering the history of changes and advances throughout the analysis process. Considering data and models, the history of data movement and transformation over time and model changes are used to externalize knowledge. For visualization components, the history of graphical views as well as of previous actions and commands serve to reproduce workflows and facilitate other users to understand the system better (Ragan et al. 2016). Thus, knowledge is not only externalized from a single system interaction, but also continuously over the history of system usage.

3.1.3 Combination

Explicit knowledge can be found in different sources, and so the process of combining different types of explicit knowledge is important (Wang et al. 2009). While the combination of different data sources is the result of an action taken by a user, the process of combing data is typically carried out by the system itself (Figure 1 - Combination). Wang et al. (2009) point out that the following must be accounted for to maintain the quality and integrity of combined products of explicit knowledge: the combination of unrelated or incorrect knowledge can degrade the trustworthiness of the system; in addition, it can decrease the quality of the knowledge represented in a visualization. To increase the overall quality and provenance, Federico et al. (2017) suggest increasing collaboration between system users and tracing and verifying relationships between multiple data instances and derived knowledge products.

3.1.4 Internalization

Sacha et al. (2014) argue that experts can generate insights and formulate hypotheses when interacting with a VA system, which can be linked to internalization. Internalization in VA systems occurs in a process leading from the system towards the user. While interacting with the system, users gather relevant evidence to relate this information to prior knowledge, which ideally results in a finding (Endert et al. 2012). This process is closely related to sensemaking (Pirolli and Card 2005) in which, through the interaction with a system, users can explore possible connections between the data, investigate and test hypotheses, and ultimately gain insights. If a finding matches or does not match a previous hypothesis, the mental model of the user changes, which leads to another system interaction or an insight (Chang et al. 2009). In this context, the system interacts with the user by enabling the observation of the visualization, the verification of the model, or the inspection of the data (Figure 1 - Internalization).

Observation: In the visualization of the processed data, units of information are presented by the system
in a way that users can perceive them, to focus their attention (Keim et al. 2008). Here, the user is able to discover patterns in the representation of the data (Green et al. 2009). Since the model can change the visualization, observations are also influenced by the reasoning of the model.

**Verification:** The model aids in collecting relevant evidence to verify a hypothesis that previously was created by the user. The model results can be evaluated by comparing them to data that represent a real-world scenario. If desired, users can define alerts, so the VA system notifies them of changes in the data. Even though the generation of a hypothesis is initiated by the user, the model plays a significant role in neutralizing cognitive biases, shortening the process of analysis, and contributing to the detection of new patterns previously hidden (Green et al. 2009).

**Inspection:** The interaction with the visualization and the model can lead to a hypothesis that can be evaluated only through interactions with the data. Since it is possible that neither the visualization nor the model represents reality adequately, the user can apply rules directly to the data to collect further evidence that supports a hypothesis (Fayyad et al. 1996).

4 Application of Our Theoretical Framework to the Case of VIMA

Our case study shows the application of the theoretical framework we have described to the project VIMA (Virtual interactive manufacturing assistant). We first describe our case study approach (Section 4.1) before we introduce the context and scope of the VIMA project (Section 4.2) and the data collected (Section 4.3). Finally, we present our findings (Section 4.4) and summarize the implications for organizational knowledge creation (Section 4.5).

4.1 Methodology

We aim to evaluate our theoretical framework (Figure 1) and to use it to reveal and conceptualize novel mechanisms influencing organizational knowledge creation through the frequent interactions between humans and a VA system. Since this process is difficult to observe outside of organizational contexts, we chose a case study approach for an in-depth investigation of the subject matter. A case study is an empirical research approach that enables the analysis of a specific phenomenon within its environment, especially when the boundaries between the practical context and the phenomenon are not clearly evident (Yin 2014). It is useful if the research is not well developed and particularly where the examination of context and dynamics are important (Darke et al. 1998). Case studies, furthermore, can be applied to investigate casual relationships and are a suitable instrument for studying context-rich sociotechnical systems (Yin 2014).

We follow a exploratory single-case study approach (Yin 2014) in which both the phenomenon under investigation and the researcher are assumed to be independent (Sarker et al. 2018). Exploratory case studies are built upon general theories – in our case Nonaka’s and Takeuchi’s (1995) theory of knowledge creation – that exist to formulate propositions, which are novel mechanisms of knowledge creation in the context of organizational knowledge creation in combination with VA. We chose to carry out a single-case study examining the case of a car manufacturer rolling out a VA system. The chosen case represents a common project among the transformation of many organizations towards a digital company and is suitable for our investigation according to Yin’s rational for single-case study designs (Yin 2014). We collected data from different sources that are derived with different methods to capture a wide range of phenomena and processes relevant to our study to ensure its validity (Bonoma 1985).

4.2 Context and Scope

The organization in our case study is a leading automotive manufacturer based in Germany. Like many of its competitors, the manufacturer is investing considerable resources into the development of electric vehicles. Dedicated analytics and engineering teams work collaboratively on establishing automated data-driven manufacturing processes to support this transformation. The units of analysis, in this case,
are one department responsible for the manufacturing of electrical energy storage systems, one department for electrical engines, and a supporting data analytics department. We refer to the overall company as AutoCorp, and these units (departments) as AutoCorp Storage (ACS), AutoCorp Engines (ACE), and AutoCorp Analytics (ACA), respectively. AutoCorp faces a quality-control challenge in its manufacturing process. It aims to resolve this challenge by improving the quality of their process in a project spanning all three units.

At present, the components AutoCorp produces are controlled for quality at specialized testing benches, which are optimized to minimize false negatives. During quality assessments, these test stations determine whether tested components meet the quality criteria. If they pass, they are labeled as “OK”; otherwise, they are labeled as “NOK” (not okay). False negative classifications have more severe implications than false positives in producing components for the automotive industry. However, both error types have a negative influence on product quality and cycle times and thus on the costs of the overall manufacturing process.

The project proposed by AutoCorp aims at using models, trained on production data and developed by AutoCorp Analytics, to improve the classification capabilities of the test benches. Building such models requires ACA to access the (tacit and explicit) knowledge of domain experts. To generate and externalize this knowledge, vast amounts of complex high dimensional data sets, comprising machine signals and manually generated annotations of datapoints referring to produced parts, must be analyzed manually by experts. The goal of the VIMA project is to minimize the current error rate of the quality control process (regarding false positives and false negatives) and reduce the additional workload for domain experts from AutoCorp Storage and AutoCorp Engines.

VIMA is a human-in-the-loop VA system that aims to enable domain experts to classify components and generate new knowledge about the underlying business processes. The goal of the system is to visualize huge amounts of high-dimensional, complex machine data, detect anomalies in the manufacturing process, and suggest possible classes for according data instances. VIMA thereby helps with the generation of labels and the discovery of relevant features that can be used to build models. In addition, it supports domain experts in their analysis of parts produced and in generating new knowledge. VIMA was released on March 1, 2020 and is being used by both ACS and ACE. Since its launch, it is continually enhanced by ACA in close cooperation with ACS and ACE.

4.3 Data Collection and Coding

The case study was carried out over a nine-month period. We collected machine sensor-data of AutoCorp’s manufacturing process, which underlies the system, conducted semi-structured interviews, and made direct observations. Sensor data comprised 524 recorded measurements of 2,543 electrical engines (98 GB disk space) and 132 measurements of 206 electrical energy storage systems (69 GB of disk space). The sensor data were used as only input for VIMA to enable experts to conduct multiple explorative analyses. Details about VIMA and its input data can be found in (Eirich et al. 2020).

We conducted seven semi-structured interviews with four domain experts for electrical engines and three with electrical energy storage systems experts. These interviewees were males between ages 24 and 33, had a mean work experience of 9 years, and had worked for AutoCorp for 7 years and 8 months on average. Each expert had a background in mechanical or electrical engineering, and they all indicated a lack of familiarity with data analytics methods. All interviews were held in person and lasted an average of 50 minutes. We questioned interviewees about socialization, externalization, combination, and internalization processes in the context of developing testing procedures for electrical components using VIMA. The interview guidelines comprised 24 questions on the process of knowledge creation during interviewees’ daily routines and interactions with VIMA in all stages of knowledge conversion and creation. (Due to space limitations, the full set of questions is not included in this study.) The interviews were recorded, transcribed, and analyzed deductively by the interviewer post hoc. The coding of the interviews was carried out by one researcher according to Hsieh’s and Shannon’s (2005) method of the direct content analysis. In this approach, an existing theory is used as a guide for initial codes to further
enhance the theory deductively (Hsieh and Shannon 2005). In our case, we used Nonaka’s and Takeuchi’s (2000) SECI model and the relations between all four SECI phases to discover novel mechanisms of knowledge creation in the context of organizational knowledge creation in combination with VA.

An on-site researcher made direct observations of the processes being studied and recorded his findings on a weekly basis, following Someren’s et al. (1994) Think Aloud Method, through which experts are asked to express their thoughts during their use of a system (Someren et al. 1994). We undertook this with experts from ACS and ACE using VIMA and transcribed the results. We used this additional data source to gain a better understanding of how experts used VIMA and how tacit and explicit knowledge was transformed between system users and VIMA as well as between system and non-system users.

4.4 Findings

At the beginning of the development of VIMA, experts from all three business units (ACS, ACE, and ACA) had to learn the language and technical methods used in the other units. During January 2020, a first prototype was developed by ACA and adapted regularly in close cooperation with experts from ACE and ACS to ensure a shared understanding of VIMA and to enhance the system continually. After this period, the first version of VIMA was deployed by ACA and made available to experts from ACS and ACE. While most use cases carried out with VIMA required substantial in-depth analysis of multiple dependent measurements requiring detailed expert knowledge, we have chosen to show use cases that serve as good examples but will also be easy to understand for readers with no mechanical engineering background. Our results are presented in the following section.

4.4.1 Socialization

Before the launch of VIMA, all the experts regularly sought advice, as part of their daily routines, from other colleagues with in-depth knowledge about specific product details, especially those in R&D departments. After VIMA was introduced and as the experts we studied became increasingly familiar to its functionalities, we observed greater socialization efforts between system users and experts from new domains. The goal of these interactions was to verify assumptions, conduct more detailed inspections of databases, or engage in joint modeling efforts to improve manufacturing processes. As one expert noted, “The visualization showed me something I did not understand, but after consulting a colleague it helped me to better understand the problem.” Another interesting type of interaction occurred with colleagues from similar domains. Staff of ACE and ACS reported that VIMA provided them with knowledge that increased their bargaining power in meetings or helped them better communicate tacit knowledge. Thus, after the launch of VIMA, socialization was triggered through an interaction with the system, which sometimes resulted in new interactions, which affected a situation not directly related to the initial interaction. For example, experts who interacted with VIMA made new findings and thus often consulted with other experts to discuss these findings; in doing so, new knowledge for experts not associated with VIMA was created. As one domain expert noted, “At first I did not understand the result of VIMA. However, after calling my colleague, who had a more detailed background of the problem domain I got a better understanding of the initial result.”

4.4.2 Externalization

At the beginning of the VIMA project, experts reported that they externalized tacit knowledge mostly through the documentation of product specifications. Domain experts did this because they wanted to make explicit knowledge available to others at AutoCorp and store knowledge for later use. However, new externalization mechanisms emerged through interaction with VIMA. Rather than dispersing knowledge in the form of documentation, explicit knowledge was stored in the system’s database in the form of features, labels, and models. After multiple analyses, experts from both ACS and ACE discovered new, highly relevant features with which to detect specific error types. In addition, the visualizations provided by VIMA revealed previously unknown anomalies in the manufacturing process, where
parts could be labeled with corresponding error types. Since these labels were the result of an analysis that could be performed only by experts with tacit knowledge about the part, the labels represent a manifestation of aggregated tacit knowledge. Further, insights derived from the use of VIMA were translated into models that improve the automated assessment and description of product behavior. One domain expert provided an example: “If the structure-borne noise of our engine increases, the unbalance also increases.” Just like labels, models denote an aggregation of complex knowledge about product behavior. In contrast to labels, models represent the decision process behind a classification, and thus are a valuable new source of explicit knowledge within AutoCorp.

4.4.3 Combination

Before VIMA, combination of explicit sets of knowledge was primarily carried out by domain experts, working manually. This included combining documents from organizational databases, which often resulted in small sets of explicit knowledge with small and incremental novelty. The combination of high-dimensional sensor data recorded during assembling steps was a time-consuming task and hence not often done by the experts. Thus, resulting data sets contained information only about a few produced parts. VIMA’s data-processing pipeline was able to process high-dimensional machine sensor data automatically across the entire manufacturing process, resulting in new comprehensive sets of explicit knowledge. These data sets included information about thousands of produced parts from multiple test stations, which could be filtered by the experts to obtain the most relevant information. In addition, these data sets were used as a source of new inputs to conduct analyses with the system. As one ACE expert said, “Now, for the first time, we can combine measurements of different sensors across multiple assembling steps.” Whereas previous data sets had come from single test stations or documents, new explicit knowledge products emerged from the combination of multiple machine sensors across the entire manufacturing process. This did not hold for tacit knowledge, however, which is always bound to individuals.

4.4.4 Internalization

Experts reported that at the beginning of the project they internalized knowledge as a result of incremental learning processes or experiences from previous product development cycles. In addition, they indicated that this process was the result of consciously performing a predefined task, such as reading documentations or consulting a colleague. During the interaction with VIMA, experts from ACS and ACE reported a continual learning process. Throughout these frequent interactions, experts described several findings that, when combined with previous domain knowledge and advice from colleagues, resulted in several insights and “ah-ha” moments (Chang et al., 2009).

Insights were often quite small, as in the case of one ACS expert who found that temperature and voltage, measured during a production process, were not correlated, but independent – in contrast to previously held beliefs. In other cases, insights resulted in formulations of hypotheses, such as “an increased resistance of a battery module decreases the measured current of an electrical energy storage system.” Testing these hypotheses created tacit knowledge for the domain experts, since their mental model changed and understanding of the problem increased. This knowledge was quite relevant for the improvement of the system, as it resulted in new valuable features, labels, and improved underlying models for VIMA.

4.5 New Mechanisms for Organizational Knowledge Creation

Based on the application of our theoretical framework to the case study, we derive new mechanisms that should be considered for organizational knowledge creation. They are summarized in Table 1.
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<th>Socialization</th>
<th>Nonaka and Takeuchi (2000)</th>
<th>New mechanisms for knowledge creation</th>
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</thead>
<tbody>
<tr>
<td></td>
<td>Knowledge is created as a result of the interaction between individuals and their exchange of tacit knowledge through shared experiences.</td>
<td>Knowledge is created as a result of the interaction between individuals and the system; the interactions can result in knowledge creation between system and non-system users.</td>
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<tr>
<td>Externalization</td>
<td>Externalization is triggered by dialogue or collective reflection. Knowledge is externalized consciously in interaction and articulated via images, symbols, and language.</td>
<td>Externalization is triggered by a system interaction. Knowledge is externalized consciously and unconsciously; it is articulated through features, labels, and models.</td>
</tr>
<tr>
<td>Combination</td>
<td>Combination is mostly executed manually and is thus limited to relatively small data sets.</td>
<td>Combination is mostly executed automatically and is thus extended to relatively large data sets.</td>
</tr>
<tr>
<td>Internalization</td>
<td>Internalization is triggered by an individual’s inherent wish to accumulate organizational know-how. Explicit knowledge must be actualized via action and practice (e.g., reading documents or “learning-by-doing”).</td>
<td>Internalization is triggered by the system’s notification of changing data instances. Learning is performed by interpreting the system’s representation of data and the formulation and evaluation of hypotheses.</td>
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**Table 1: New mechanisms for organizational knowledge creation from system interactions**

During the interaction between individuals, information is interpreted by each individual to become knowledge. VIMA is not able to create knowledge alone; rather, it transforms available data into information and interprets it in a way that creates meaning. Through the interaction of domain experts both from ACS and ACE with the system and each other, we observed the conversion between tacit and explicit knowledge that enhanced the knowledge base of the users and improved the system.

Nonaka and Takeuchi (2000) argue that socialization is a result of direct social interaction; for example, individuals exchange tacit knowledge through hands-on learning experiences. In our case, socialization was triggered through system interactions and often resulted in the creation of new knowledge for individuals using and those not using the system. After multiple analyses with the system, users approached other colleagues to verify assumptions or discuss findings, and VIMA mediated the exchange of tacit knowledge between these individuals. Traditionally, tacit knowledge is externalized consciously through physical interaction, articulated through images, symbols and language. In turn, VIMA facilitates the externalization of tacit knowledge, such as by requiring users to label data. It then combines various labels into larger collections of externalized knowledge, which are then transformed into recommendations and visualizations that are supplied to a wide audience of users. This combination of continuous externalization, automated combination, and visualization affects the internalization of knowledge by VIMA’s users. Multiple different sets of explicit knowledge are recombined and reconfigured manually and often contain comparable small data sets. In turn, we observed that combination efforts were mostly carried out by VIMA, with huge data sets recombined into smaller, more comprehensible ones that were easily interpretable by its users. Nonaka and Takeuchi (2000) describe the process of internalizing explicit knowledge as similar to “learning by doing,” in which an individual is driven by the inherent wish to learn something new. We observed something different: as experts conducted observations, verifications, and inspections of the data, there was a learning process through which explicit knowledge from data, models, and the visualizations was transformed into new tacit knowledge, such as changed mental models regarding the users’ problem domains.

**5 Discussion**

To gain a better understanding of the process of organizational knowledge creation and conversion in the context of interplay between humans and VA systems, we presented a theoretical framework, which we evaluated with a case study. To address our research question, we outlined traces of new mechanisms.
for organizational knowledge creation that extend the existing theory of organizational knowledge creation (Nonaka and Takeuchi 1995). Based on our framework (Figure 1), our study results, and resulting derived mechanisms for knowledge creation, we formulate and discuss the following propositions.

1) **New tacit knowledge is created through socialization between individuals as a result of system interactions with one user and a VA system, from findings, insights, actions, or hypotheses.**

Since the creation of tacit knowledge is bound to individuals, VA systems are not capable creating this kind of knowledge. However, VA systems can trigger interactions between multiple individuals through which new tacit knowledge can be created. We observed in our case study that these interactions were resulting from findings, insights, actions, or hypotheses. Actions, for example, resulted from system interactions in which users made specific observations that resulted in new findings. In many instances, these findings were discussed with one or multiple other individuals not related to the VA system itself, through which new insights or hypotheses emerged. After these discussions in particular, the resulting hypotheses were tested using proper statistical tests that met the criteria for objectivity, which resulted in new tacit knowledge for individuals involved in these analyses. We thus argue that even though tacit knowledge is bound to individuals, VA systems trigger socialization cycles, which is not considered in the established mechanisms of socialization articulated by Nonaka and Takeuchi (2000).

2) **Tacit knowledge is converted into explicit knowledge by means of externalization through VA system interactions via manipulating visualizations, training models, or preparing data, and are articulated through features, labels, and models.**

Since tacit knowledge plays a focal role in the competitiveness of organizations, how organizations can create conditions that enable the externalization of tacit knowledge (Haldin-Herrgard 2000) is important. We believe that VA systems can contribute significantly in this context and facilitate the conversion from tacit to explicit knowledge via visualization manipulations, training models, and preparing data. The advantages of VA systems, such as fast filtering of data, adapting interfaces after interactions, and making recommendations based on trained models can be combined with human tacit knowledge. The resulting knowledge products features, labels, and models, play an important role in organizational knowledge management and complement well-established but, from our point of view, rather generic explicit knowledge products such as images or symbols (Peltokorpi et al. 2007). Even though features, models, and labels are addressed by many researches (Amershi et al. 2014; Chegini et al. 2020; Jackle et al. 2016; Schneider et al. 2018; Suschnigg et al. 2020), their value for organizational knowledge creation during externalization processes has not previously been considered. Thus, organizations should take these knowledge products into account, since they resemble the aggregation of multiple complex sources of tacit knowledge (Bernard et al. 2018).

3) **New explicit knowledge is created through combination abilities of VA systems, in databases, models, or visualizations.**

The synthesis of data from multiple sources is an often addressed topic across multiple research communities, such as information technology (He et al. 2010), information systems (Skillicorn and Wang 2001), and pattern recognition (Adhikari and Rao 2008), to name a few. However, to the best of our knowledge, our theoretical framework is the first that relates organizational combination efforts of explicit knowledge to VA systems. Our case study reveals that an automatic combination of complex multidimensional data was carried out by a VA system, with the results used to trigger learning and interaction cycles. VIMA recombined overwhelming amounts of information into smaller data sets. Thus, we believe that VA systems can create explicit knowledge by providing models and visualizations to the user and storing resulting knowledge in databases. Such knowledge can be created from user interaction with the system by for example adapting models, or automatically, by for example querying databases and presenting recombined results through visualizations. We hence follow the proposition of Wang et al. (2009) that organizations not only should support the synthesis of complex data into cohesive sets of new explicit knowledge but also introduce systems that facilitate the recombination of huge data sets and encourage their validation through experts.
4) Explicit knowledge is converted into tacit knowledge in internalization as a result of inspecting data, verifying models, or observing visualizations in VA systems.

The process of converting explicit knowledge into tacit knowledge can best be described as “learning” (Endert et al. 2012; Nonaka et al. 2000). To support learning, VA systems should provide the ability to look at data from different perspectives. This enables users to collect versatile evidence and increase the level of trust in findings or insights (Sacha et al. 2014). In our study, we observed that such learning processes were afforded via system interactions through inspecting data, verifying models, and observing visualizations. In this regard, we agree with Amershi et al. (2014), who stress active user involvement when introducing systems, which can augment cognitive reasoning. In our study, the resulting mutual interaction between humans and machines resulted both in overall continuous system improvement and additional knowledge for its users. Thus, when fostering knowledge creation, organizations should not only consider how to improve the collaboration between their employees but also how to include a system that absorbs externalized knowledge over time. The resulting explicit knowledge should be incorporated into models that proactively guide users’ decision-making and knowledge creation processes, which are closely related to the notion of provenance in VA by Endert et al. (2012).

We acknowledge that our study has some limitations. The case is dedicated to one company in the automotive industry. Since our study analyzes organizational knowledge creation and conversion afforded by VA systems, our approach is likely to affect the generalizability to knowledge creation and conversion of other context-related systems, such as business intelligence systems. The interpretation of our results is also constrained to our small and biased sample size (i.e., seven male participants). Because VA systems are often designed to tackle very specific domain problems, they naturally address relatively small user groups. Thus, our study results do not allow for drawing any conclusion regarding the empirical validity of our framework beyond our application domain. Even though other described process models (Sections 2.1 and 2.2) address the conversion and creation of knowledge, they take either a system or organizational perspective. We believe that our theoretical framework combines the strengths of both areas and contributes to explaining organizational knowledge creation with VA systems in manufacturing settings.

6 Conclusion and Future Work

In conclusion, we provide novel mechanisms for organizational knowledge creation that are the result of the interaction between humans and a VA system. To derive these mechanisms, we first integrated the process of knowledge creation in VA (Sacha et al. 2014) and the process of organizational knowledge creation and conversion (Nonaka and Takeuchi 1995) into an integrated theoretical framework that accounts for both the interactions between humans and the systems and those between non-system-related individuals. We then conducted out a case study for a 9-month period, collecting data from multiple sources (sensor data, semi-structured interviews, and direct observations). Our findings reveal that the conversion between tacit and explicit knowledge is affected by interactions with VA systems. The resulting novel mechanisms for organizational knowledge creation were clearly noticeable in each phase of the SECI model (Nonaka and Takeuchi 1995). Our derived theoretical framework and novel mechanism for organizational knowledge creation serve as a guiding framework for further research.

Finally, although our findings inform the theory of organizational knowledge creation and conversion, additional research is needed to extend this theory. For example, we focus on a single stakeholder group for our VA system, but research suggests that externalized knowledge in particular can affect other stakeholders within an organization (Markovic and Bagherzadeh 2018). Thus, future research should consider how to diffuse this kind of knowledge to other related stakeholders (e.g., suppliers, analytics departments, or management) and analyze the effect on stakeholders beyond the application domain.
References


Knowledge creation through visual analytics


