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ManuKnowVis: How to Support Different User Groups in Contextualizing and Leveraging Knowledge Repositories

Joscha Eirich, Dominik Jäckle, Michael Sedlmair, Christoph Wehner, Ute Schmid, Jürgen Bernard, and Tobias Schreck

***Abstract*—We present ManuKnowVis, the result of a design study, in which we contextualize data from multiple knowledge repositories of a manufacturing process for battery modules used in electric vehicles. In data-driven analyses of manufacturing data, we observed a discrepancy between two stakeholder groups involved in serial manufacturing processes: Knowledge providers (e.g., engineers) have domain knowledge about the manufacturing process but have difficulties in implementing data-driven analyses. Knowledge consumers (e.g., data scientists) have no first-hand domain knowledge but are highly skilled in performing data-driven analyses. ManuKnowVis bridges the gap between providers and consumers and enables the creation and completion of manufacturing knowledge. We contribute a multi-stakeholder design study, where we developed ManuKnowVis in three main iterations with consumers and providers from an automotive company. The iterative development led us to a multiple linked view tool, in which, on the one hand, providers can describe and connect individual entities (e.g., stations or produced parts) of the manufacturing process based on their domain knowledge. On the other hand, consumers can leverage this enhanced data to better understand complex domain problems, thus, performing data analyses more efficiently. As such, our approach directly impacts the success of data-driven analyses from manufacturing data. To demonstrate the usefulness of our approach, we carried out a case study with seven domain experts, which demonstrates how providers can externalize their knowledge and consumers can implement data-driven analyses more efficiently.**

***Index Terms*—Design study, H.5.2 [Information interfaces and presentation]: User interfaces–graphical user interfaces (GUI), user-centered design, visual analytics in manufacturing.**

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I. Introduction

VISUALIZATION has an intrinsic motivation and longstanding tradition of applied and problem-driven research [30]. The typical goal of such projects is to enable domain experts to understand and analyze their own domain data through carefully designed visualization interfaces [44]. In other words, data expertise is brought to domain experts through interactive visualization. While this scenario still resonates well with many classic scientific setups, with the advent of data science now also collaborative setups are becoming more common, in which data scientists and domain experts collaborate toward a joint solution. Instead of enabling domain experts directly, the main challenge in such setups lies in bridging the knowledge gap between differently-skilled stakeholder groups. We argue that visualization plays a key role in bridging the gap between stakeholders with different levels of knowledge and we report on an example of such a multi-stakeholder design study from the automotive industry.

This industry currently faces fundamental changes due to the digitization of its production processes [25], where data-driven analyses are already firmly integrated into industrial manufacturing processes [24]. Recent success stories show how such analysis efforts result in substantial manufacturing improvements. Examples are the visual exploration of assembling line performance to detect inefficiencies [54], the analysis of acoustic signatures of electrical engines to improve manufacturing quality [12], or the identification of patterns in machine repair logs to decrease maintenance costs [20]. However, data-driven analyses exist that cannot be executed by only one stakeholder group alone. As a results, there exists a knowledge gap between those that *provide* knowledge, and those that *consume* it (See Fig. 1 top left). We will study exactly this discrepant relationship within a real-world scenario of the automotive industry.

Knowledge *providers*, such as engineers, have domain knowledge about specific parts of the manufacturing process. For instance, they know exactly what data is recorded at manufacturing stations. However, *providers* do not have the necessary skills to perform sophisticated data-driven analyses, such as the training of machine learning models. Such analyses are usually performed by highly skilled data experts, such as data scientists. However, this group does not have first-hand domain knowledge about the manufacturing process. For example, we interviewed seven data experts, who reported that for previous

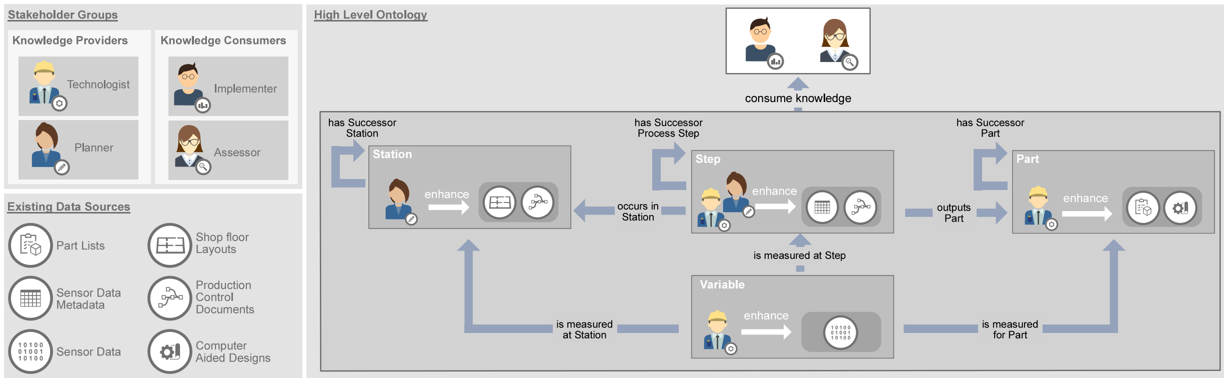


Fig. 1. Relevant stakeholders, data sources, and high-level ontology for ManuKnowVis. Technologists and planners provide and implementers and assessors consume knowledge. We use six different data sources as input data for ManuKnowVis. A manufacturing process can be described with the entities ”Station”, ”Step”, ”Part”, and ”Variable”. Each entity can be represented with existing data and enhanced by providers. Consumers can inspect this high-quality process knowledge to improve analysis outcomes.

data-driven analyses they required knowledge about a robotic arm location inside a manufacturing station that might contain an error or about the interconnection of battery cells for different derivatives of battery modules. Therefore, they rely on consuming knowledge, which is why we refer to them as *consumers*.

Instead of enabling *providers* directly via visualization interfaces, the main challenge in manufacturing setups is to bridge the knowledge gap between these two groups and foster fruitful, effective, and seamless collaborations. While such setups have been rarely reported in visualization studies so far, we argue that these setups will become increasingly common and thus also important for the visualization community. The goal of our work is to report an example of such a multi-stakeholder design study in collaboration with the BMW Group to illustrate the value that visualization can add to such scenarios. In this regard, we report the challenges *consumers* face when accessing manufacturing knowledge and how *providers* can leverage visualization interfaces to externalize their knowledge.

At the beginning of each data analysis project, *consumers* strongly rely on gathering relevant information, such as where relevant data is located. In theory, *providers* can support *consumers* with exactly this knowledge. However, we observed that *providers* and *consumers* have different mental models and thus required a long time to find a common language as the foundation for a discussion. *Consumers* can also study existing documentation about the manufacturing process, such as process flow diagrams. However, these documents are often complex while *consumers* also manually have to join many data sources to get a holistic overview of the manufacturing process. Thus, even though rich valuable repositories of knowledge exist, *consumers* find it hard to access and comprehend these repositories. As a response, we propose ManuKnowVis (Manufacturing Knowledge Visualization), a *visualization* system [18] that resulted from a design study [44] project in collaboration with *providers* and *consumers* at the BMW Group.

We base our study on existing documentation from different data sources, which give a holistic depiction of an assembly line for battery modules from one of the BMW Groups's manufacturing facilities. Furthermore, we base our study on an existing ontology that served us as a baseline to model existing data sources with ManuKnowVis. *Providers* can use ManuKnowVis to enrich existing manufacturing entities with their knowledge by describing and connecting entities. ManuKnowVis provides them with visual interfaces to externalize their knowledge [35], [52], such as grouping stations via annotation functionalities directly on shop floor layout images. *Consumers* can use ManuKnowVis to get a detailed understanding of distinct data-driven analyses they are addressing. *Consumers* can inspect annotations to answer questions such as *how are different stations connected* or *what property of a product do specific variables measure?* Therefore, ManuKnowVis bridges the gap between *providers* and *consumers* by supporting *providers* in externalizing their knowledge in a systematic and structured way and by providing *consumers* with efficient access to knowledge, which was previously inaccessible.

In summary, we contribute 1) the problem abstraction about accessing knowledge for a manufacturing process; 2) the design of ManuKnowVis, which supports *providers* in externalizing their knowledge and *consumers* in accessing knowledge; and 3) the evaluation of ManuKnowVis with a case study and reflections of our design process.

II. Related Work

First, we summarize related work about knowledge management systems in the context of industry 4.0 (Section II-A) and design studies in the automotive sector (Section II-B).

A. Knowledge Management Systems in the Context of Industry 4.0

Industry 4.0 refers to the creation of networks of interconnected machines and processes in manufacturing enterprises with the help of information and communication technologies [55]. This infrastructure provides an unprecedented opportunity to connect different data-generating instances from manufacturing processes. The goal is to achieve the effective digital integration of the entire manufacturing enterprise [53]. Recorded data can be used for several purposes, such as predictive maintenance [6], [9] or energy efficiency management [36], [45], [51], to name a few. Thus, instead of machines that simply perform routines, within industry 4.0, machines are capable of communicating with each other and collaborating autonomously [17].

One important resource to cope with such complex and fully digitized manufacturing systems is expert knowledge. This knowledge, however, is provided by various stakeholder groups inside organizations, for example about the machine and product properties or data-driven analyses [13]. Hence, the efficient management of these distributed knowledge repositories is a key resource for the successful digitization of manufacturing processes [15], [59].

In this regard, Knowledge Management is a productive series of iterative and systematic exploitation and exploration activities, which aim to make information actionable and reusable [1], [16], [32]. Here, knowledge can be divided into two types: *explicit* knowledge that can be externalized easily, for example, in words or numbers; and *tacit* knowledge that is inherent to the individual [15], [18], [35], [52]. The latter is often not recognized by the individual as knowledge but rather expressed through action, commitment, and involvement, which renders it notoriously difficult to externalize [18].

Despite the efforts to reflect Knowledge Management contributions to organizational learning, in the era of Industry 4.0 it has not been widely studied so far [1], [2], [58].

For example, in a recent literature review Fakhar et al. [17], pointed out that constantly-connected manufacturing environments comprising machines that monitor processes continuously and produce reports also increase the potential for knowledge creation exponentially. As a result, substantially more unstructured data and information are recorded and congest organizational information systems. In our research, we aim to contribute to the body of knowledge management in the context of industry 4.0. To do so, we contextualize explicit and tacit knowledge of various stakeholder communities within an industry 4.0 setting. By contextualizing, we mean setting the knowledge in context with other data sources.

B. Design Studies in Automotive Industry

Visualization to date has contributed substantially to help to analyze complex data in manufacturing settings, as the recent survey by Zhou et al. [57] shows. A key domain is the automotive sector. There, design studies and resulting VA applications mainly support product design, condition monitoring of stations, the optimization of testing procedures, or the visual support of high cognition tasks. Efforts were carried out to visualize in-car communication networks [41], [42], [43], to facilitate the exploration of multi-criteria alternatives for rotor designs [7], to detect and analyze anomalies in test stations [14], [50], the visual exploration of assembling data to detect inefficiencies [54], and to support mechanical engineers in the analysis of acoustic signatures of electrical engines [12].

Some of the mentioned studies explicitly acknowledge the need for externalizing *tacit* expert knowledge [14]. For example, the *Cardiogram* system [43] stores externalized expert knowledge in the form of state machine diagrams, while *IRVINE* [12] stores expert knowledge in the form of labels for electric engines and annotations in the raw sensor data. All mentioned studies succeeded in creating insights for engineering experts based on machine sensor data. The problem we face, however, is how *consumers* with a much lower level of engineering knowledge can leverage expert knowledge. Grounded on previous findings, we built a system that processes, combines, and contextualizes different *explicit* knowledge repositories, which are enriched with *tacit* knowledge from multiple *providers*. The resulting combined knowledge is available for *consumers* through visual interfaces, which supports them in better performing data-driven analysis.

III. Methods

During this study, we primarily followed Sedlmair et al.'s nine-stage framework for design studies [44]. In addition, we used the *Nested Model* for visualization design and validation by Munzner [34], which guides a more detailed problem characterization, the data operation and abstraction, the visual encoding and interaction design, and the algorithm design.

To understand the domain problem, we performed online interviews with seven *consumers* and seven *providers*. We asked *consumers* about how they perform data-driven analyses, what kind of challenges they face, or which information they need during such projects. Regarding the *providers*, questions were about what information is generally important when analyzing manufacturing data or what general documentation tasks they perform in their daily business are. The interviews helped us in understanding and abstracting the domain and the domain problem of missing knowledge during data-driven analyses.

To describe production processes and involved stakeholders, we relied on an existing ontology from the BMW Group. The ontology provided us with a formal baseline to represent manufacturing data with ManuKnowVis. A detailed description of the ontology and how knowledge sources are embedded into it is provided in Section V-A.

Our system development went through three main iterations over five months, during which we interviewed *providers* and *consumers*, tested design alternatives, and held discussions with visualization experts. Each iteration was carried out in close collaboration with two *providers* and two *consumers*. They accompanied the system development with knowledge about the data characterization (Section IV-C), and resulting tasks (Section V-C). They also gave a constant stream of feedback on the visual design of our system. The exchange with each expert took place in up to two meetings per week ranging from 30-90 minutes. During these meetings, characterization and design aspects were discussed and open issues were clarified. We evaluate ManuKnowVis with a case study. Methodological details for this downstream evaluation are provided in Section VIII.

IV. Problem and Data Characterization

We report the characterization of the problem domain about transferring knowledge between *providers* and *consumers*.

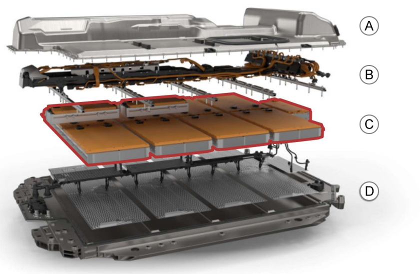


Fig. 2. Electrical energy storage system consisting of four main parts cover (A), module contacting system (B), battery modules (C), and cooling system (D). In our design study, Battery Modules (C - red outline) are the targets of our analysis.

First, we introduce the manufacturing processes we analyzed (Section IV-A), Next, we describe the problem our collaborators face (Section IV-B) and the data we included (Section IV-C).

A. Background on Analyzed Manufacturing Process and Stakeholders

In our design study, we will analyze data from the manufacturing of electrical energy storage systems as part of a car battery (see red outline Fig. 2).

Each individual subcomponent is produced during hundreds of manufacturing steps. An example of such a step is the stacking of individual lithium-ion cells together into packs of 40 cells to form a battery module. These manufacturing steps are performed at various physical manufacturing stations. An example of a station is multiple collaborating robotic arms, which paint lithium-ion cells to shield and protect them against external influences. To increase manufacturing output, stations run in parallel and execute the same manufacturing steps. For example, multiple robotic arms are all involved in the step cell painting. Thus, a station represents a physical entity, while a step represents the process performed by the station. At each station dedicated sensors record variables. For example, at the same painting station, sensors record the temperature inside the station, the thickness of paint layers, and the voltages of each battery cell after painting.

In terms of the relevant stakeholder groups involved in the manufacturing of battery modules, we interviewed seven *consumers* in charge of coordinating data-driven analyses, performing data analyses, or building data infrastructures. In addition, we interviewed seven *providers* responsible for the planning of manufacturing processes or specific stations in an assembly line.

Characterization of Consumers: After interviewing the *consumers*, we learned that they could be divided into two overarching groups *implementers* and *assessors*, which are outlined on the top left in Fig. 1. All had a background in computer science and can be described as follows:

Implementers are required to perform data-driven analyses. They are highly skilled at data-related tasks, such as data visualization (e.g., the development of dashboards for manufacturing data), data engineering (e.g., setting up data infrastructures to store machine sensor data), or sophisticated data analyses (e.g., training machine learning models to predict manufacturing output quality). They are interested in specific information about the manufacturing process, for example, the functionality of a single station or where to find variables for a step.

Assessors evaluate and prioritize data-driven analysis projects and assign *implementers* to them. For them, it is important to have a high-level overview of the manufacturing process, for example, to ensure that data from all manufacturing stations are recorded properly.

Characterization of Providers: In our design study, we surveyed that the most relevant *providers* are planners and technologists (See Fig. 1). All planners and technologists have a background in mechanical or electrical engineering and can be described as follows:

Planners have general knowledge about the manufacturing process as a whole integrated system. They know where stations and steps are located, how they are connected, and how parts are flowing through assembly lines.

Technologists have detailed knowledge about individual steps in the manufacturing process. They know what individual stations do, what variables they measure, and what kind of parts are produced.

B. Domain Problem

The challenge of accessing manufacturing knowledge is present across the manufacturing sector [7], [12], [33], [42]. Like many companies, the BMW Group is also investing large resources in the digitization of its processes. In this regard, *consumers* and *providers* face the following challenges when investigating existing data sources or interacting with each other:

Investigate Existing Data Sources: The interviewed *consumers* and *providers* reported that existing documentation is often perceived as *complex* for other stakeholders with no background in the same domain. As one implementer noted *"I had a case where several sensor recordings, such as temperatures or voltages were related to the same variable. Only after consulting a colleague, I found out that this was because the values were actually points on a time series curve of a variable."*

Another challenge from existing data sources is that *consumers* often do not know *where to find relevant information*. Furthermore, *information is fragmented* across multiple tools, which are not integrated. Hence, there is not only a single location to find all relevant information. In this regard one assessor mentioned that *"sometimes documentation can be scattered across different databases. Hence, we sometimes have difficulties finding out if we have all relevant information at our disposal."*

a) Access different documentation tools: Providers reported that they need to use *non-unified documentation solutions*, such as local files, to document their knowledge. This makes it even harder for *consumers* to *access existing documentation*, while *providers* find it *tedious to document* their knowledge. Here, one *technologist* reported that *"[we] do not have a system, which can easily join data from multiple databases.*

Having such a system at hand would ease documentation efforts for the manufacturing process".

Request Support of Providers: Consumers and *providers* reported that due to their background, they also have *different mental models*. Here, one technologist explained that *"especially when data-driven analyses start, we do not have a common language. I remember that we had a kick-off meeting, where all participants needed more than 40 minutes until it was clear what we were talking about"*. Furthermore, *providers* are often hard to reach, where one assessor noted *"we had a project where timelines between us and engineers were challenging to align risking a delay"*.

Due to these challenges, it is relevant for *consumers* to access knowledge about the manufacturing process more effectively. In turn, *providers* need a way to easily support their documentation efforts.

C. Data Sources

Providers and *consumers* reported that they consider the following heterogeneous data as important to give a holistic overview of the manufacturing process.

Production Control Documents: In these documents, planners describe manufacturing steps (e.g., welding or gluing) and the sequence of how stations perform these steps. This information is relevant to know what is done at stations and how they are related to each other.

Sensor Data Metadata: When conceptualizing an assembly line, technologists specify what variables are recorded at stations. This includes information about variables (e.g., what unit the variable has or at which step a variable is recorded). That information is relevant to know what kind of variable is recorded and how it can be interpreted.

Computer-aided designs (CAD): When designing new products, technologists produce various CADs, which are images showing the products. This information is relevant to understanding how the parts - being the core object of many analyses - look like. In this study, we got access to 2D projections of CAD files.

Shop floor layouts: Each manufacturing plant contains various shop floors, where parts are produced and assembled. Here, planners arrange stations in shop floor layouts. This information is relevant to review at which stations parts are assembled into new parts and how stations are related. Basically, this data can be represented as a graph structure with nodes containing X and Y coordinates that are connected by edges

Part lists: When designing new products, technologists do not only provide CADs for individual parts, such as battery cells but also information on how parts are arranged to form another part (e.g., a battery module contains battery cells and heat-conducting plates). This information is relevant to understanding how parts are related to each other with this clearly defined hierarchical structure.

Sensor data: Technologists specify what kind of data must be recorded inside each station, to monitor either the station itself or the parts it produces (e.g., multiple temperature or voltage recordings). So basically, this data can be seen as multivariate numerical time series data

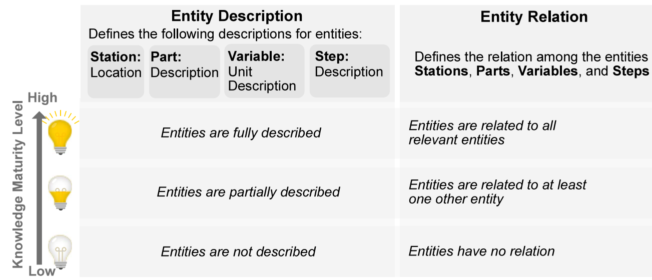


Fig. 3. Knowledge maturity levels of ontology entities. Entities either need a description or must be related to other entities.

V. Abstractions

Based on the domain problem and the used data sources, we provide further abstractions. First, we relate users and data to an existing ontology (Section V-A). Next, we develop Knowledge Maturity Levels as the main goal of ManuKnowVis (Section V-B). Last, we abstract tasks, which aim to support *providers* in externalizing their knowledge and *consumers* in accessing this knowledge (Section V-C).

A. Data Characterization

The high-level ontology, depicted in Fig. 1, outlines how we abstracted from existing data sources and how users interact with such data sources. The ontology comprises four entities (station, step, part, variable) and describes an assembly line of a manufacturing process. Steps, such as gluing or welding, occur in stations and output parts. To represent the sequence of steps, stations, and parts, these entities can have a successor. For example, station 2 can follow station 1. Variables are measured at steps and stations and help to evaluate parts.

The existing data sources (see Section IV-C) already provide a description of entities and their relation in the ontology. For example, part lists indicate how parts are assembled into new parts. Since the existing data may be incomplete, *providers* can enhance each entity in light of their own knowledge. For example, a planner can use ManuKnowVis as a visual editor to arrange stations on a shop floor layout or technologists can assign a unit to a variable. While *providers* enhance each entity of the ontology, *consumers* can inspect each entity and the relations between entities to better understand aspects of the manufacturing process. For example, an *implementer* can analyze what variables belong to a step or an *assessor* can check in which step a part is produced.

B. Knowledge Maturity Levels

The goal of ManuKnowVis is to enhance knowledge about entities of the ontology (See Fig. 1). We refer to this as *knowledge maturity levels*. To compute maturity levels for each entity, we were guided by the available data sources (See Section IV-C). For example, the shop floor images include the location of stations but no information about part flows. As such, we can use shop floor images to describe stations but not parts. As a result, we derived the necessary information for each entity in Fig. 3,

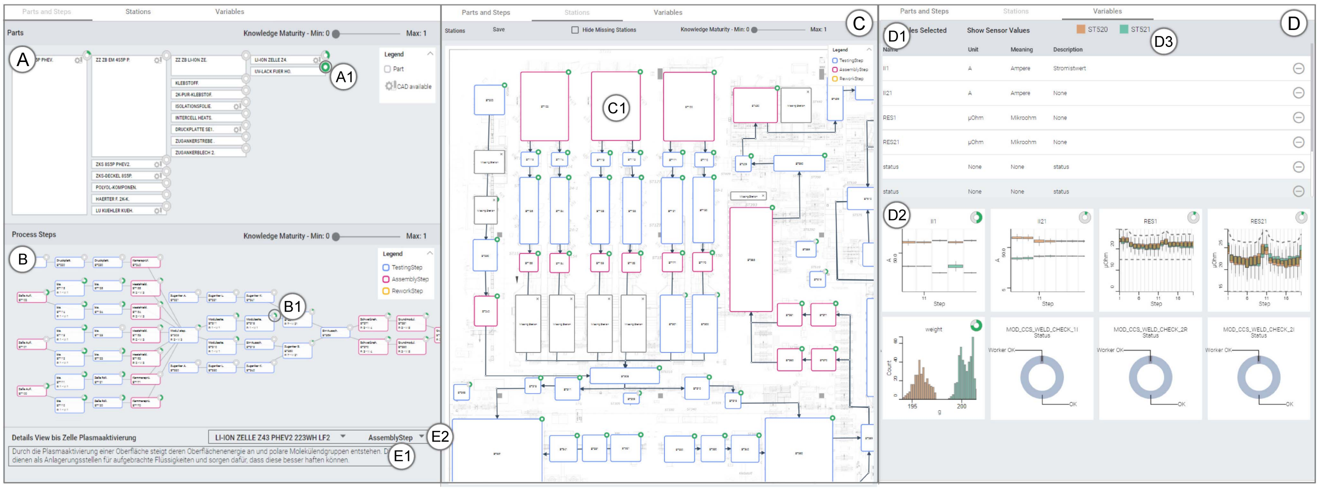


Fig. 4. The ManuKnowVis system. On the user's desktop screen two views are shown side by side, where users can freely switch between each view using the navigation panel on top. ManuKnowVis is divided into four views aligned to all entities from Fig. 1. *Parts* are displayed as an icicle plot in (A). *Steps* are shown with a Sugiyama layout in (B). Stations are displayed in (C) and arranged following the physical layout of an assembly line, which is shown as a background image. Selected variables for a *part*, *step*, or *station* are displayed in (D). Metadata variable attributes are shown in (D1) and their distribution in (D2). Depending on their type, variables are displayed as histograms, multiple boxplots, or donut charts. Knowledge maturity levels are shown as donut charts (e.g., A1, B1) in the views (A), (B), (C), and (D). Details for entities are displayed in (E).

which is necessary to achieve a sufficient *knowledge maturity level*.

Entities can either be provided with a *relation* or a *description*. In terms of entity descriptions, a station needs a location on the shop floor. Parts, variables, and steps all need a description, while variables further require a unit. Furthermore, entities need a relation to other entities. For example, a variable can be measured for a part, a station can have a successor, or a step can be executed by multiple parallel running stations.

As a result, we can compute the *knowledge maturity* for each entity by checking what information is necessary to fully enhance it. In Fig. 3, for instance, a variable needs a description and a relation to one part. If a *provider* adds a description and a unit, the *knowledge maturity level* is 66%.

C. Task Abstraction

We present the abstracted tasks that serve as primary design targets for ManuKnowVis. *Providers* (P-T) and *Consumers* (C-T) interact differently with ManuKnowVis, which is why we differentiate between their tasks below:

P-T1 Describe Entity: Providers need to describe each entity in the ontology. They can describe entities in multiple ways, such as text inputs or annotations.

P-T2 Connect Entity: To define the relationships among entities, *providers* also need to connect different entities. Entities can be connected by assigning different kinds of entities to each other, such as a step to a product, or by connecting entities with the same type, such as a station to a successor station.

C-T1 Overview of Entities and Relations: Consumers need to locate relevant entities in the manufacturing process, for example, where a step of interest is executed. Furthermore, *consumers* need to evaluate how entities are related, such as which stations belong to a part.

C-T2 Drill-Down and Expand: Consumers exploring large numbers of entities need support for the drill-down to entities of interest. The information needed may differ between the location of stations or the distribution of measured variables. After an entity of interest is identified it needs to be evaluated in the context of other entities, for example, what other stations also measure variables of the same unit. Thus, *consumers* also require support to expand back to an overview.

C-T3 Hypothesize: Consumers need to constantly be able to confirm or reject hypotheses. Such hypotheses can regard single entities, for instance, *what unit does a variable of interest have*, or multiple distinct entities, such as *how is the data quality of all variables for a product*.

VI. The ManuKnowVis System

We present the design and implementation of ManuKnowVis. All views are shown in Fig. 4. We use the notation A-E to refer to the views and sub-components (e.g., A1, B1) later on. (A) shows available "Parts", B "Steps", C "Stations", D "Variables", and E details for the views A,B,C. Apart from E, each view represents an entity from Fig. 1. Two views are always displayed side by side. Users can switch between the three views using the top panel in Fig. 4. All views include zooming and panning functionalities to ease navigation.

The goal of an analysis is either to enhance knowledge-maturity levels or increase knowledge about entities. We display knowledge-maturity levels as donut charts in all views (e.g., A1, B1), where the green area indicates the completeness of an entity. Hovering over the donuts displays a tooltip indicating to which degree an entity is completed and which information is missing. As outlined in Section V-B, we compute the knowledge maturity degree by inspecting how much information for each entity is provided according to Fig. 3. As soon as *providers*

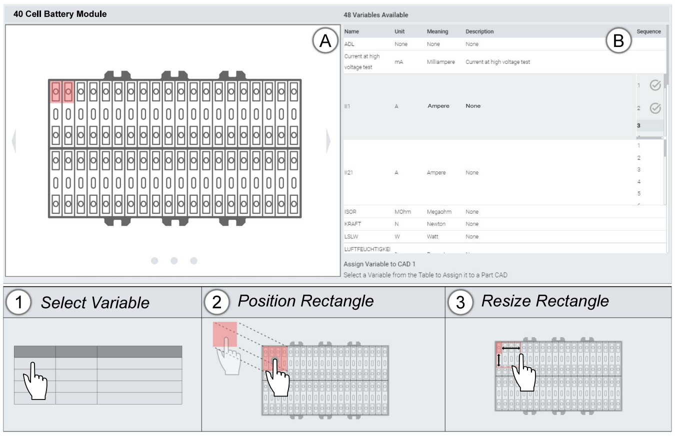


Fig. 5. Details dialog for parts. (1) shows available CADs for a part and (2) its variables. Providers can connect both entities by executing the steps (1) → (2) → (3).

have enhanced an entity, its *knowledge maturity* representation updates in each view. Filters for maturity levels are available on the top right of A, B, and C.

The views (A,B,C) represent an entry point into an analysis, while (D,E) show details from previous selections [46]. Each view for an entity of Fig. 1 can either be used for an individual analysis or combined in a workflow switching between multiple views. For example, by starting analyzing a part (A) and then reviewing all stations (C) for the part followed by an analysis of variables (D) from a station of a part. Hence, we first will provide a description of each individual view A-E (Sections VI-A, VI-B, VI-C, VI-D, VI-E) before outlining interaction workflows between the views (Section VI-F). Each Section closes with an exemplary workflow of how users can interact with the view based on observations we made during the system development. For the views, we used the showcase data set from an assembly line for battery modules containing the described data sources from Section IV-C. Due to non-disclosure agreements with the BMW Group, we anonymized all data.

A. Parts

Parts are represented by an icicle plot in (A). A legend in (A1) shows, which parts contain a CAD object. Selecting such parts gives users the opportunity to open up a new dialog (A2), which is shown in Fig. 5. In this dialog, consumers can inspect available CADs (see Fig. 5(A)) and recorded variables (see Fig. 5(B)) for this part. Parts can have multiple CADs, which are shown as in a carousel view. Variables can either be single measurements or recorded as a "sequence" of dependent measurements. An example of a single measurement is the recording of a single temperature value. In turn, an example of a sequence is resistance values recorded at each battery cell of a module containing 40 cells.

Furthermore, *providers* can relate variables to locations on the part in the CAD dialog. This is important since some variables only measure specific part properties, which can only be accessed at certain part locations. For example, the resistance of a cell can only be measured at its welds on the minus and plus pols.

To provide this relation, *providers* have to follow a three-step process. First, they need to select a variable from the table (see Fig. 5(1)). Next, a rectangle appears directly on the CAD (see Fig. 5(2)), which can be freely moved on the CAD via dragging. Finally, *providers* need to resize the rectangle by dragging its borders (see Fig. 5(3)). Of course, steps 2 and 3 can be executed multiple times and change in their order. When the rectangle is positioned and saved, it is directly available for later changes or analyses. We quote this linking from variables to parts as *annotations*, since one is "annotating" the CAD by drawing a rectangle on it. Annotations are valuable to *consumers* since they enable them to relate variables not only to a part but also to a specific region of interest on the part.

An exemplary workflow, we observed during the usage of the parts view was the following. *Providers* were asked to enhance parts for battery modules. Thus, they first observed the hierarchy of the icicle plot. Next, they selected a specific sub-component deeper in the hierarchy from the icicle plot, for example, a cell contacting system as a sub-component of a battery module. To select an appropriate CAD for annotations, they evaluated how individual CADs looked like using the carousel feature. Furthermore, they evaluated what variables were recorded, for example, resistances and voltages. Finally, they selected resistance variables and added annotations by following the steps (1-3) from Fig. 5.

B. Steps

Steps are shown as a sequence that can be executed by multiple stations in parallel (B). We display this sequence with a Sugiyama layout [11]. We draw the sequence of steps on the horizontal axis from left (start of the assembly line) to right (end of the assembly line). On the vertical axis, we draw the stations so that different stations can be shown in parallel. Stroke colors indicate the step type (pink: testing step, blue: assembly step, yellow: reworking step).

An exemplary workflow, we observed during the usage of the steps view was the following. *Consumers* wanted to evaluate what steps existed and how they are related. Thus, they interacted with the steps view via zooming and panning. They also used the slider for knowledge maturity levels (upper right of (B)) to filter for steps with high knowledge levels. Finally, they looked for specific steps, such as electrical testing steps for battery cells, and analyzed the respective step descriptions in the details view, which we demonstrate in detail in Section VI-D.

C. Stations

Stations are displayed as rectangles on top of the real shop floor image as a node-link diagram (C). To do so, we first extract the x and y coordinates, as well as the width and height of each station rectangle from the shop floor image using computer vision. To extract the coordinates, as well as the height and with, we apply the library *OpenCV* [8]. Next, we extract the name of each station from written strings on the image with the neural network *tesseract* [47]. As a result, we position station rectangles according to their original position on the shop floor where we use the same color coding as in (A, B). Stations that are available on the shop floor but not in other data sources are displayed as *missing stations* with gray rectangles. The position of stations can be changed at any time by dragging a station rectangle. Width and height can be adapted by dragging its borders.

As a next step, providers need to connect stations to their successor or predecessor stations. This is done by first clicking on a rectangle and then dragging a line to another station rectangle. This results in a straight line between the two stations. However, in the real assembly line, station links are not always straight lines. Hence, we allow to freely adapt each line by setting individual breakpoints on lines to draw lines "around corners".

An exemplary workflow, we observed during the usage of the station view was the following. *Providers* were asked to first evaluate if the positions of the stations from our computer vision based preprocessing were correct. Stations, which were positioned in wrong locations on the shop floor were repositioned by *providers* via dragging and resizing the station rectangles. Next, providers connected stations to their successors or predecessors by drawing lines as explained above between stations.

D. Details for Parts, Steps, and Stations

In addition to the individual part, steps, and station views, we provide another view to enhance and inspect these entities. By selecting an entity from (A, B, C), its details are displayed in (E). (E1) shows entity descriptions as text area and (E2) additional entity attributes as a drop-down. For example, in the case of steps, these attributes are step types (testing, assembly, or reworking step) and parts that are outputted by the step. Both can be changed at any time. An exemplary workflow, we observed during the usage of the details view was the following. *Consumers* were browsing through the part, step, and station views and evaluated details considering certain entities they selected. For example, one *consumer* wanted to know what the step "plasma activation" from (B) means and reviewed in the details view the following description. "The plasma activation is a necessary step to prepare battery cells for painting. In this step, the battery surface is treated with plasma so that it is cleaned and paint molecules stick better to it."

E. Variables

Variables for parts, steps, and stations can be displayed by selecting either one from these entities and then clicking on the button "show sensor values" on the top left in (D). This displays all variables in a table view in (D1) and the distributions of senor recordings in (D2). Besides the name of a variable, the table view also includes metadata attributes, such as the unit, the meaning of the unit, and a description of the variable. These attributes can be changed at any time.

We show distributions on a grid and differentiate between the following three variable types: Categorical variables, (e.g., *status ok* versus *status not ok*) are displayed as donut charts. Numerical variables (e.g., one temperature recording for multiple parts) are displayed as a histogram. Sequence variables (e.g., multiple numerical recordings for multiple parts) are displayed as a sequence of boxplots. Regarding histograms, we use 20 bins according to the empirical studies and guidelines of Shanann et al. [39]. To inspect the same variable for parallel running stations, users can add additional station recordings by clicking on a button "show neighbor stations" on top of (D). This replaces the button with a legend of available stations with the colors green, orange, and blue. Furthermore, it displays additional recordings on top of each grid cell in (D2) for each station. In our design study, we never encountered situations where more than three stations recorded the same variable. To overcome visually overlapping variable recordings for parallel stations, users can filter for single stations by selecting individual stations in (D3).

An exemplary workflow, we observed during the usage of the details view was the following. *Consumers* wanted to know if the available variables for lithium-ion cells were suitable for a model. As a result, they clicked on the part "lithium-ion" cells in the part view, and next the button "show sensor recordings" in (D). Furthermore, they wanted to know how the variable was distributed at different stations and clicked the button "show neighbor stations".

F. Linking of Views

All entities from Fig. 1 are linked. Hence, we also want to provide this linkage in our visualization design and provide a close linking of all views from ManuKnowVis. By doing so, we aim to implement a drill-down and expand workflow, where *consumers* select an entity from one view, drill down to an entity of another view and then again expand to a different view to analyze how this entity is related to other entities. The same linking also supports *providers* in identifying where to find entities that must be further enhanced. Hence, our linking mechanisms are included both for the enhancement and the inspection of entities, which we outline in detail in the following:

Enhancing Entities. The change of an entity also affects the entities to which it is connected. For example, connecting stations in (C) also changes the step view in (B) by adding more steps to the Sugiyama layout. Another Example is the annotating of CADs, which we mentioned in Section VI-A. Here, the information of the annotation is also saved for the variable and thus available during the inspection of variables.

Inspecting Entities. Inspecting one entity with ManuKnowVis also highlights all related entities in other views. We achieve this by including hovering mechanisms. Hovering over an entity in each of the views, highlights related entities in the other two views. An example is provided in Fig. 6. Here, a battery cell is selected in 1) and according steps are highlighted in 2) and stations in 3) (red outline in Fig. 6). Regarding variables, we display existing CAD annotations as a tooltip. By hovering over histograms or columns of boxplot sequences in (D2), the according CAD and the provided annotation are shown as demonstrated in Fig. 7. In (A) the first column of the distribution is selected and the according annotation is shown on the first battery cell of the CAD of a 40-cell battery module. In (B) the 20th column

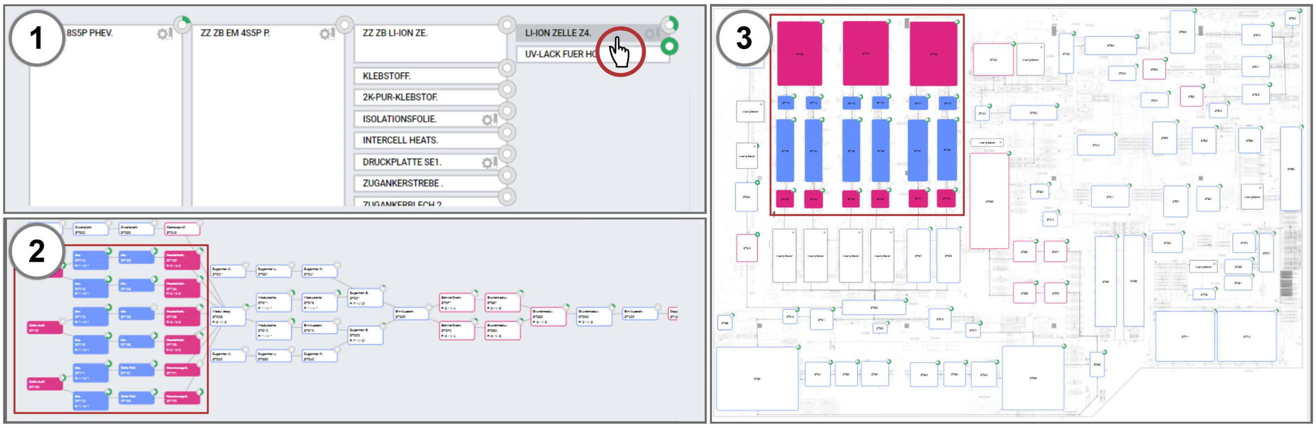


Fig. 6. Linking of one entity (part) to related entities (steps and stations). Hovering over a part in (1) highlights its steps (2) and stations (3).

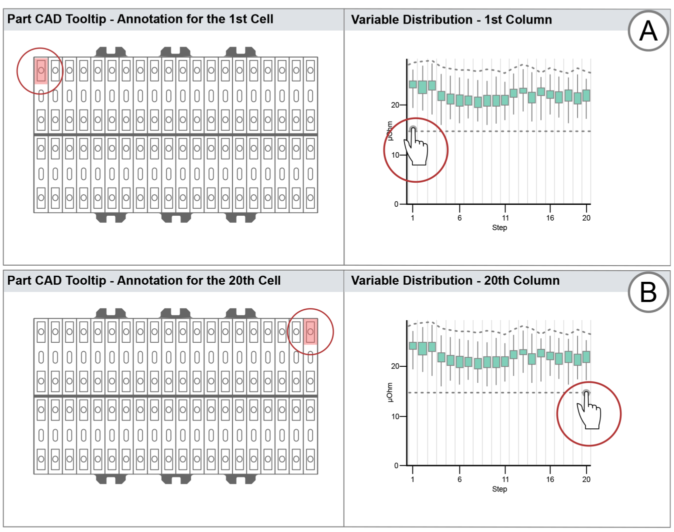


Fig. 7. Tooltip to show the relation of a variable to a part. Hovering over the 1st column in (A) displays the annotation on the 1st battery cell for the battery module CAD. Hovering over the 20th column in (B) displays the 20th battery cell for the CAD.

is selected and the according annotation is shown for the 20th battery cell in the CAD.

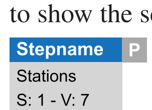
One typical workflow we observed during the usage of our linking mechanisms was the following. *Consumers* wanted to know more about variables recorded for the part battery cell. Hence, they hovered over this part and reviewed all existing stations. Next, they also inspected the highlighted steps and clicked on individual steps to inspect their descriptions. Finally, they selected one step and inspected the variables that were recorded during this step.

VII. Design Iterations

ManuKnowVis was designed and developed during three main iterations. In the following Section, we will describe each iteration in detail:

Iteration 1: Many applications of ontology-based systems are visualized with a force-directed layout [10]. Furthermore, Landesberger et al. [27] found out that a force-directed layout is a visualization approach that is usually well adopted by users, who are not that well educated in sophisticated visualization sciences. Since, we also rely on an ontology and dealt with users with little experience in sophisticated visualization science, at the time of the first iteration, we also experimented with a force-layout [37], [48], which is shown in Fig. 8(1). In this approach, we focused on visualizing steps as a sequence, where green and purple strokes indicated the step types (assembly and testing step). In the same graph, we also represented stations with a blue stroke (1a) and the assembly line with a red stroke (1b). Selecting a step from the graph unfolded its stations (See red outline in Fig. 8(1)). However, *consumers* and *planners* reported that displaying all entities in a graph was confusing since they all have to be interpreted differently. Furthermore, users reported that edge crossings made the results incomprehensible. Regarding our color coding, one of our collaborators reported having color deficiencies and was not able to distinguish between different entities.

Iteration 2: In the second iteration, we first adapted our color scales to account for color deficiencies [31]. Next, we aimed to show the sequence of steps and stations in a more organized



manner avoiding edge crossings. Instead of focusing on steps, we intended to display a sequence of nodes containing high-level information about parts, steps, and stations of an assembly line (*C-T1*). On the top of each node, we showed the step name, then stations, and below that the number of sub-processes (S) and variables (V). Parts (P) were displayed as gray rectangles on the right side of a node. As outlined in Fig. 8(2), we displayed nodes as a sequence with line breaks.

However, *consumers* and *providers* reported that displaying steps as a sequence in one line was not correct, since this did not reflect the real situation of a manufacturing process. Furthermore, *consumers* and *providers* reported that they found it difficult to identify the relationship between different nodes and wished to separate parts, steps, and stations, which is why we decided to provide different views for each entity.

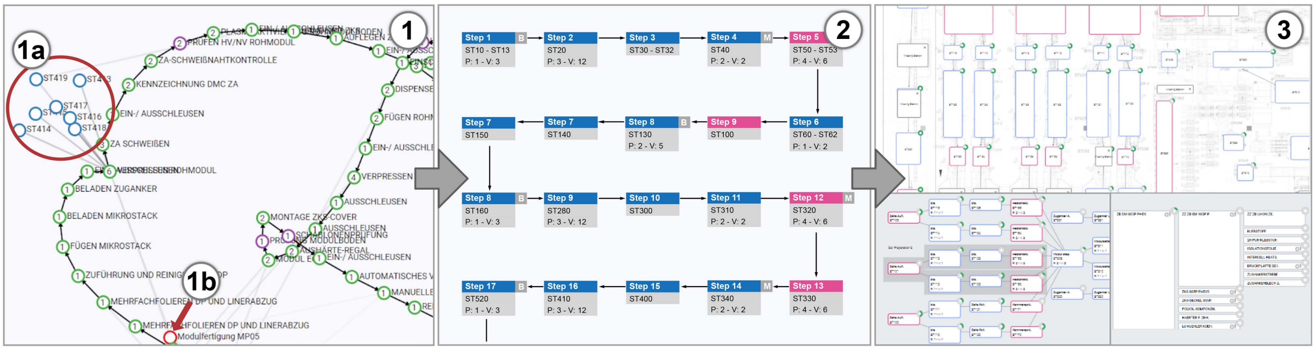


Fig. 8. Evolution of step and station sequences. In the first attempt in (1), we used a force layout, which we changed to a directed sequence of nodes containing steps and stations in (2). In (3), we display parts, steps, and stations in individual views.

Iteration 3. In the last iteration, we separated parts, steps, and stations for an assembly line in separated views as shown in Fig. 8(3). All three entities contain a hierarchical data structure. Therefore, we experimented with several hierarchical visualization designs to represent parts, steps, and stations. Regarding parts, we tried out hierarchical node-link diagrams or table views. However, we found that icicle plots turned out to be the most adequate and space-conserving choice to represent this specific entity [27]. This design choice was also most liked by our study collaborators. Since, a part is composed of several sub-parts, for example, a battery module containing lithium-ion cells, isolation films, and glue, we consider this representation appropriate. Regarding the steps view, we also experimented with node-link diagrams or table views. Nevertheless, we found that a Sugiyama representation is more appropriate since it is specifically designed to display hierarchical relations and avoids edge crossings. In terms of the station representation, a node-link representation directly on top of the shopfloor layout turned out to be most appropriate, since it represents the reality of the real manufacturing process for battery modules.

VIII. Evaluation

We provide examples of how our approach supports *providers* and *consumers* with a case study. Case studies are a method to dive deep into a specific domain to provide insights into a phenomenon within its environment [19], [44], especially when the practical context and the phenomenon are not clearly evident [56]. Considering the problem and the users, we are interested in how ManuKnowVis helps *providers* in externalizing their knowledge and how *consumers* can leverage this previously inaccessible knowledge to better perform data-driven analyses. Since these processes are difficult to observe outside of organizational context, we consider a case study as an appropriate approach [26].

Participants: We performed the case study for an assembly line for battery modules in collaboration with seven participants (two female, five male). The demographics of our study participants are shown in Table I. For the *providers*, we recruited one *planner*, with general knowledge about the entire assembly line, and two *technologists* responsible for specific manufacturing stations in the same assembly line. For the *consumers*, we recruited three *implementers* involved in data-driven analyses from the assembly line and one *assessor*, who evaluated data-driven analyses about the assembly line. The study participants were between 28 and 40 years of age. Two *consumers* worked at other companies before starting at the BMW Group. Regarding the seniority of working directly at the BMW Group, our study participants worked at the BMW Group for between three and eight years. However, compared to their seniority in other fields, almost all participants were relatively new in the field of the manufacturing of electrical vehicles. Hence, especially the consumers were in many cases in more need of manufacturing knowledge.

TABLE I
Demographics of Our Study Participants

	Gender	Role	Age	Years in Electric Mobility	Years at BMW	Years of Experience before BMW
Provider 1	Female	Planner	34	2	7	0
Provider 2	Male	Technologist	33	6	8	0
Provider 3	Male	Technologist	28	3	5	0
Consumer 1	Female	Implementer	30	1	4	0
Consumer 2	Male	Implementer	37	4	4	7
Consumer 3	Male	Implementer	40	3	3	10
Consumer 4	Male	Assessor	38	1	8	0

Data: For the case study, we uploaded data from all six described data sources of Section IV-C. In this regard, a battery module consisted of over 15 parts (e.g., heat-conducting sheet, battery cell). For eight parts, CAD drawings were available. Parts were produced at over 50 steps, manufactured at over 100 stations, and contained over 1,000 variables. Furthermore, we uploaded sensor measurements from 753 randomly selected battery modules.

Procedure: First, we performed kick-off meetings with all study participants to introduce all features of ManuKnowVis. Sessions were held online and took from 60 - 90 minutes. After that participants used ManuKnowVis for two weeks. The case study was separated into two phases. In the first phase, we asked *providers* to document entities in the form of describing and connecting entities. After that, in the second phase, *Consumers* were encouraged to analyze entities and evaluate whether they were able to use available information for data-driven analyses. The data-driven analyses were about identifying whether cell

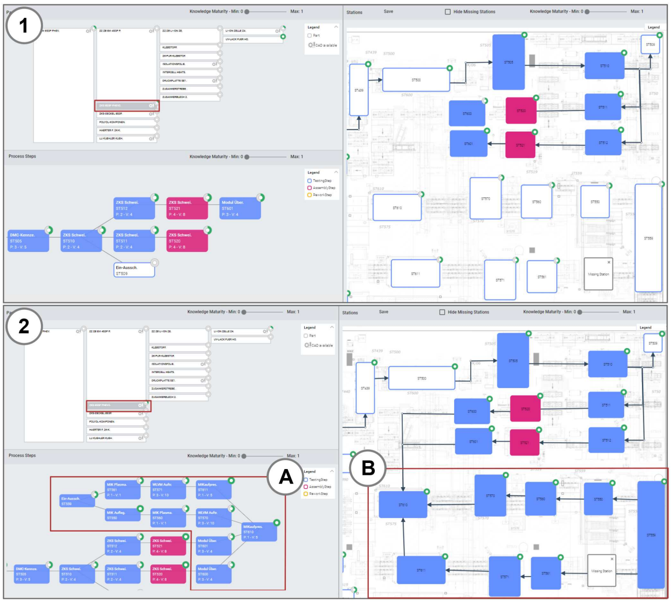


Fig. 9. Connecting stations for cell contacting systems. (1) shows the part, step, and station view for a cell contacting system as the selected part (red outlined on the top right). Hovering over the part in (1) reveals that in the station view connections are missing. In (2), a provider connected all missing stations for the part cell contacting systems (red outline in part view). (A) shows the step view that adapted automatically after connecting more stations in (B).

contacting systems were correctly attached to battery modules and the evaluation of cell thicknesses for their compression into modules. After the study, we interviewed *providers* and *consumers* to evaluate how ManuKnowVis supported them with their tasks. To quantitatively assess the usability of the system, we also applied the system usability scale (SUS) [28]. Due to our small sample size, the SUS scale does not provide empirical evidence of the usability of our visualization but rather a rough direction to support the assumptions of our design choices.

A. Results for Providers

To demonstrate how *providers* used ManuKnowVis to externalize knowledge, we first provide a real example we observed during our evaluation in Fig. 9. In (1), the *provider* started hovering over parts in the part view and reviewed, which steps and stations were highlighted in the respective views. He noticed, that when hovering over the part "cell-contacting system" (top red outline in (1)) some stations were missing for this part. Hence, he first connected the missing stations in (2). This resulted in an automatically adapting step view in (2B). Next, he selected the newly appeared steps and saw in the drop-down of the details view (See (E2) of Fig. 4 that no part was assigned to them. Hence, he assigned the part "cell-contacting system" to the steps. After hovering over the same part in (2), more steps (2 A) and stations (2B) are highlighted in their respective views. This information was then stored in ManuKnowVis and available for further usage by other *provider* and *consumers*.

Furthermore, *providers* described how ManuKnowVis supported them in their documentation efforts. Especially the feature of connecting variables to parts was noted as helpful where one *provider* noted that *"I cannot remember how often we executed the exact same annotation task, where I drew rectangles of CAD images and saved them on my local file storage"*.

Furthermore, *providers* reported that documenting knowledge with ManuKnowVis would impact data-driven analyses positively where one *provider* made the following example: *"I am currently involved in an ongoing data analysis project with two technologists and another data scientist. In this project, we have to do the same analysis for a large data set every three months. However, every time we have to do this analysis, we somewhat have to start from the beginning because we have to figure out which exact part we have to analyze, which variables are recorded, and how the variables are related to the part. Using ManuKnowVis would have saved us a lot of time in the past because we could have documented exactly this information"*. Finally, *providers* were satisfied with the accuracy of how we managed to automatically position stations on the shop floor image using computer vision since only 2% of all stations had the wrong position.

That said, all interviewed *providers* reported that they found that ManuKnowVis represents an excellent addition to the tools we are using to document important information about the manufacturing process. In this regard, one provider explained that *"at the moment we have to document everything in text and tables. ManuKnowVis, however, provides a much more efficient way for our documentation, since much information is already automatically generated. We just have to fill out the missing parts. This makes it one the one side easier for us and also less error-prone."*

Providers also recommend some system improvements, which we will include in further iterations of ManuKnowVis. First, they requested to include more data sources for entities to improve their own analyses. For example, process flow diagrams show how parts circulate in an assembly line. Here, *providers* suggested tracking individual parts along with their stations in the manufacturing process. Another suggestion was to visualize multiple floors of an assembly line. For instance, sometimes parts are transferred to elevators and then continue on the ceiling of the shop floor. Even though our analyzed assembly line did not include elevators it is necessary to visualize such processes for additional assembly lines.

B. Results for Consumers

To demonstrate how *consumers* used ManuKnowVis, we first provide an real example, we observed during our evaluation in Fig. 10. The *consumer* had an analysis scenario where she needed to understand data from the case of a battery module. Hence, she selected this part from the part view (red outline upper left in 10) and evaluated which steps and stations were related to the part (A and B). During the usage, she noted that "*this is fantastic since normally I would need to look through masses of tables and join them myself. Here, I have this information immediately, which drastically reduces the amount of time I need to understand the data I am looking at.* Next, she browsed through the steps view and selected the step "*case welding*" in B1 since that step contained the most available variables. After

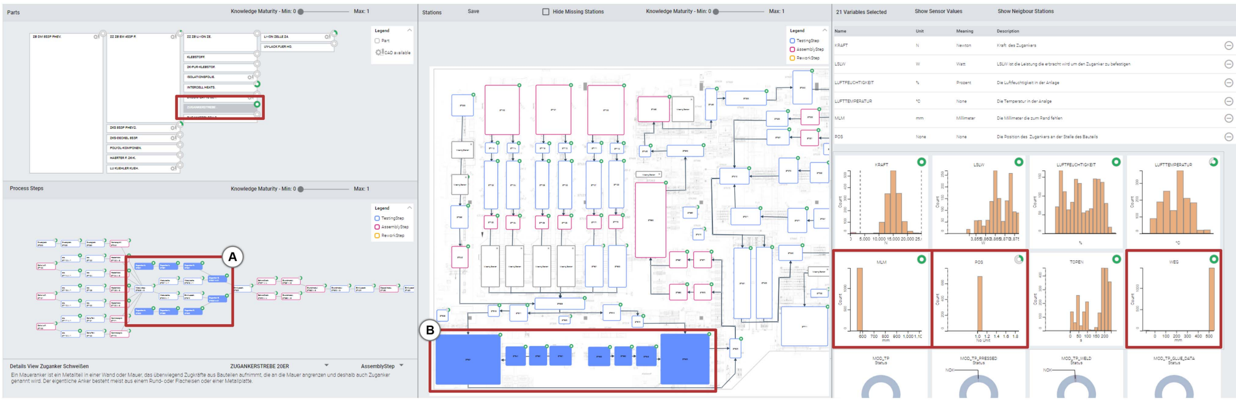


Fig. 10. Example of analyzing data from multiple linked views. For the selected battery module in (A), the steps are highlighted in (B), and stations in (C). The variables for a selection from (B1) are displayed in the variable view. Here, (D) shows variables, which only record one value and can be excluded from an analysis.

that, she switched the station with the variables panel and plotted all variables. During that analysis, she noticed three variables, which she could exclude from her analysis because they only recorded the same value (see the red outline on the right in Fig. 10). Furthermore, she reported that the descriptions in the variable table helped her significantly in better understanding the variables for that step. After working with ManuKnowVis, the *consumer* reported that she was able to dive into her analysis much faster since she did not have to look up all information in distinct databases and ask *providers* for additional help in finding and understanding the data.

Furthermore, *consumers* reported that ManuKnowVis helped them in better comprehending data-driven analyses. For instance, ManuKnowVis supported them in understanding what data is currently available for the assembly line, where one *consumer* noted that "*seeing which variables for stations are available helps us in identifying which data we can use for an analysis of manufacturing data*". Furthermore, ManuKnowVis provided them with a good overall understanding of the assembly line. In this case, a *consumer* explained that "*since the station view is very similar to what planners are using it feels a little bit like we see the world through a planner's eye. This helps us in understanding how they work and what they need from us during data-driven analyses.*" Also, metadata attributes of variables, such as units were noted as helpful to understand the meaning of variables.

In addition to that success story, we outlined three other situations in Fig. 11, where *consumers* showed us how ManuKnowVis helped them in better understanding variables for data-driven analyses. Fig. 11(1) shows how coloring different stations impacts the analysis of two variables. Before ManuKnowVis, *consumers* did not make a differentiation between stations. However, in some cases, this differentiation is necessary, since due to distinct calibrations of stations, stations sometimes measure variables slightly differently. Furthermore, ManuKnowVis supported *consumers* in identifying variables, which contain outliers (see Fig. 11(2)). Here one *consumers* mentioned that "*some variables contained some outliers, which I will have a closer look at.*" ManuKnowVis also provides information about which variables might be excluded from further analyses. For example, Fig. 11(3) illustrates one variable which always records

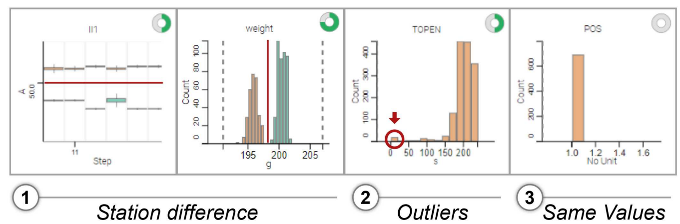


Fig. 11. Three different scenarios of how ManuKnowVis supported consumers in analyzing variables. (1) shows two variables that must be analyzed separately, since their stations perform slightly different measurements. (2) illustrates variables that contain outliers and (3) variables that record the same value are less adequate for deeper analyses.

the same value. Such variables might be of less importance for data-driven analyses.

When asking *consumers* how the knowledge-maturity degrees helped them during their analyses, they all reported that they especially used them for filtering for entities where information was already present. Furthermore, they felt more confident working with entities with high maturity degrees. Here, one *consumer* reported that "*I feel more confident if I know that all the information I potentially need is already there and that I do not have to approach other experts to get this information in person.* One reason for that could be that *consumers* we interviewed were relatively new in the field of electric mobility. In this regard, one *consumer* reported that "*especially when you are new to a specific field, such system help tremendously to better understand the context you are working in.*"

As system improvements, *consumers* suggested including a new view to visualize knowledge maturity levels of entities as ordered list to immediately see, which entities need enhancements. Furthermore, they wished to include more assembly lines to evaluate how parts, steps, and stations are related in a broader context.

C. Results From the System Usability Scale

Considering the quantitative results of the usability survey, our system provides very good usability according to the adjective equivalent of the achieved SUS score [3]. The individual scores

TABLE II
RESULTS FROM THE SYSTEM USABILITY SCALE WITH THREE PROVIDERS AND THREE CONSUMERS

	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Total
Provider 1	5	7.5	7.5	10	10	7.5	5	10	10	5	77.5
Provider 2	7.5	7.5	10	7.5	10	7.5	7.5	7.5	10	10	85
Provider 3	5	7.5	7.5	10	7.5	10	10	10	10	7.5	85
Consumer 1	5	10	10	7.5	10	7.5	7.5	7.5	7.5	10	82.5
Consumer 2	10	10	7.5	10	10	10	7.5	10	7.5	5	87.5
Consumer 3	10	7.5	7.5	7.5	7.5	10	7.5	7.5	5	10	80
Consumer 4	7.5	7.5	5	7.5	7.5	7.5	10	5	7.5	10	75

for providers and consumers are outlined in Table II. ManuKnowVis scores highest on the integration of individual views (Q5) and lowest on using the system frequently (Q1). This shows that our study participants relied on the strong focus of linked views for individual entities. A possible explanation for the results for Q1 is that once *providers* only need to use the system a few times to document all necessary entities of a manufacturing process. Once, *consumers* have gathered enough knowledge they do not need to use ManuKnowVis that frequently anymore. However, we are not able to draw a final conclusion on this observation, because of the low number of participants involved.

IX. Discussion

In this design study, we contribute to the problem characterization and abstraction of the externalization and contextualization of knowledge about a manufacturing process for battery modules. We further report the interactive design of the presented visualization system ManuKnowVis, which we evaluated together with seven *consumers* and *providers*. Our design study represents a very detailed view of the problem domain. From a more abstract point of view, we integrated a visualization system into the workflows of *providers* to support their documentation efforts and of *consumers* to help them in understanding complex manufacturing data to better perform data-driven analyses. To the best of our knowledge, the problem we described in Section IV-B about the relation between *consumers* and *providers* is unique inside the BMW Group and has not been addressed by other researchers so far. We thus argue that a design study with a detailed analysis of the problem domain and resulting abstractions was necessary to successfully support related stakeholder groups with their very specific tasks.

The overall usability usefulness of our approach is demonstrated by our high usability score and the fact that both *providers* and *consumers* reported that they were able to reach their goals outlined in Section V-B better with ManuKnowVis. Before ManuKnowVis, *providers* had to externalize their knowledge mostly manually in local documents or in personal discussions with *consumers*. In turn, *consumers* had no system at hand, that contextualizes knowledge from different databases across the BMW Group. With ManuKnowVis, *providers* now have for the first time a system at hand that drastically reduced documentation efforts for them and provides them with an interface to easily externalize their knowledge. This on the other hand is highly important for *consumers*, who now can get fast access to information they normally would only get in a very tedious manner by manually browsing through database tables, documents, and engaging with *providers* in private discussion. Our evaluation, however, is constrained by the fairly small sample size of participants. However, it is rather unusual to build solutions for specific domain problems, where more than a couple of experts are actually able to evaluate the proposed approaches as demonstrated by other case study evaluations [4], [5], [21], [29], [49]. Nevertheless, we believe that our system is a step toward bridging the gap between *providers* and *consumers* and allows *consumers* to access previously inaccessible knowledge to better perform data-driven analyses.

Although the design was specific to knowledge about one assembly line at the BMW Group, some aspects can provide guidance to the design in other manufacturing-related domains. Some of that guidance results in the following lessons learned (L) to contextualize knowledge for complex domains and design similar systems:

L1) Use Ontologies to Abstract From Data: The ontology guided us in connecting different existing data sources. For example, how stations are related to steps. All data sources are currently available at different databases at the BMW Group but before ManuKnowVis, *consumers* had to analyze documents in each database individually. Ontologies also support the definitions of knowledge maturity levels. In our case, we were able to derive the exact information necessary to complete the documentation of entities and their relations, such as stations that need a sub-line. We therefore were able to directly address knowledge maturity levels with the specific *provider* tasks, *describe* and *connect* entities. The resulting guided workflows supported *providers* in easily enhancing all used data sources. We believe that our ontology can be used by many other practitioners in the manufacturing domain. Our ontology provides a simple yet generalizable overview of many existing automated manufacturing processes that record data. For example, a manufacturing process for washing machines also contains ”stations”, ”steps”, ”parts”, and ”variables” that are related exactly as we pointed out in our paper. Considering that the same data as in our research is present, one can even use the same visualizations as we described in our research.

L2) Consider the Relation Between Providers and Consumers: In this work, we outlined the discrepancy between *providers* and *consumers* and gave insights on their interactions. We believe that the concepts of knowledge *providers* and *consumers* in data driven projects can be abstracted to various domains. For example, in the medical sector, physicians could take on the role of a *provider* by labeling medical images, while machine learning engineers could take on the role of a *consumer* to build a classifier that improves diagnosis capabilities. Even though we only analyzed a case from the manufacturing industry, our proposed concept of *providers* and *consumers* also supports researchers and practitioners from other domains to analyze the relationship between these separate user groups.

L3) Use Linked Views for Individual Entities of an Ontology: In our first attempt, we tried to build a system showing all entities of our proposed ontology and their relations in a single force-directed layout. However, our study participants reported that this did not reflect the real process of an assembly line. Hence, we propose to represent entities with simple individual views, such as tree layouts or process diagrams. This finding can be leveraged by researchers and practitioners in other domains. Instead of creating a visualization system that shows an entire ontology, visualization researchers might consider how each entity can be represented in a single view and how these views can be linked with each other. In Section VI, we provided several examples of what such linking can look like (E.g., Fig. 6).

L4) Consider Annotations to Externalize Knowledge: We present guided workflows with our visualization on how to externalize and store knowledge. Besides simple features, such as text inputs for variable descriptions, we included more abstract functionalities in the form of annotations. Here, drawing sub-lines allowed to cluster stations, while drawing rectangles on CADs allowed *providers* to connect variables to specific part regions. This form of externalizing knowledge is currently completely new at the BMW Group. It does not only help *providers* in easily performing their documentation tasks but also *consumers* involved in current analyses of manufacturing data or even outside the application domain [15]. Annotations of variables, for instance, can be queried by external stakeholders, such as suppliers in charge of developing specific manufacturing stations to evaluate how variables are related to specific regions of a part.

We believe that these four recommendations can help other researchers and practitioners when investigating similar manufacturing domains. For example, Sun et al. [49] developed the system *PlanningVis*, which also visualizes part dependencies to support the exploration and comparison of manufacturing processes. To consider the relation of parts to other entities, they could connect them via ontologies to distinct data sources that provide details about stations or variables (L1). Another application area might be building management [22]. Here, Ivson et al. [23] developed the system *CasCADe* to support engineers in analyzing the construction processes of oil and gas plants. Here, they can also rely on ontologies (L1) to connect different building entities via linked views (L2). Furthermore, they could leverage expert knowledge from engineering experts (L3) in the form of annotations (L4) for distinct building objects and their relation to the final oil and gas products.

Even though these four insights might seem rather abstract and generic, we demonstrate how they would apply to domains outside the manufacturing sector, for example in supply chain management. Here a toy example can be the field of shipping logistics. By using ontologies (L1), all providers (L2) for different containers on a ship (cars, sugar, etc.) could rely on the same semantic layer to structure their data, which facilitates the analysis of provided data later on. For example, all containers could include the variables, timestamp, product, weight, quantity, supplier, and supplier location. Next, by using linked views (L3), the cargo company in the role of a consumer (L2) could evaluate the route of a ship and which container was loaded on a ship, and where it is unloaded using the Sugiyama view or the node-link diagram. The same cargo company could also have the role of a provider (L2) by using the station view and connecting different entities (L4). For example, the station view could be changed to a world map and each station to a harbor on the map. The cargo company could then connect different harbors to annotate the routes of a ship on this map. Finally, the receiving company in the role of a consumer (L2) could use the whole visualization system to analyze, where the containers that contain the products for further storage will arrive at what destination.

In terms of scalability, we believe that ManuKnowVis already is appropriate for larger application scenarios. First, all views contain zooming and panning functionalities. This coupled with the strong linking of the views already helps users to immediately find locations of interest in the other views. For example, one could zoom out in the step and station view and hover over part of interest. As demonstrated in our paper, this immediately shows the locations of related steps and stations. Nevertheless, the individual views could benefit from some more adoptions to scale for even larger data sets.

In terms of the part view, the icicle plot already represents a space-conserving layout. Including more parts and a deeper hierarchy of parts could be addressed by including additional zoom events where clicking on a node unfolds nodes deeper in the hierarchy. Regarding the step view, one could introduce additional filters that allow the selection of specific parts of interest. For example, users could have an additional horizontal brush filter to ease the navigation in this view as demonstrated by Schwab et al. [40]. Regarding the station view, again additional filters could show distinct node-link station graphs for individual assembly lines. This, however, requires enhancing the ontology with the new entity *assembly line*. Another way to provide scalability of the station view can be to collapse all stations to one assembly line in a single rectangle. Clicking on an assembly line rectangle would then uncollapse all stations belonging to the assembly line. A similar graph-based approach is demonstrated by Reitz et al. [38]. In terms of the variable view, again additional filters and ordering mechanisms would ease the analysis of larger amounts of selected variables. For example, one could filter for sequence variables only or variables with specific units, such as only voltages.

The design also had some limitations, which we briefly summarize here. In our visualization, we use data from only one assembly line. This is because the current ontology is designed for single assembly lines. A solution for this can be the adaption of the ontology via introducing successor assembly lines, as is already the case for parts, steps, and stations. To be consistent with our recommendations of providing views for separate entities, this results in the need to introduce an additional view to also navigate between assembly lines. Furthermore, we do not consider the fact that assembly lines can have different floors to transport parts. A solution for that could be to either include different filters in the station view to show different floors or to represent the assembly line in a three-dimensional space.

X. Conclusion and Future Work

This article presents a design study on the development of a visualization approach to contextualize and leverage the knowledge of a manufacturing process for battery modules. The resulting system ManuKnowVis addresses two different user groups with distinct levels of manufacturing knowledge. *Providers* can use ManuKnowVis to externalize their knowledge via describing and connecting different entities, such as parts, steps, stations, or variables. They can do so with different techniques, such as providing text inputs or annotating entities. *Consumers* can use ManuKnowVis to access previously inaccessible knowledge to better understand data-driven analyses of manufacturing data. ManuKnowVis comprises four different views that are based on an existing ontology, which we show in Fig. 1. Here, users can select parts from an icicle plot, steps from the Sugiyama layout, or stations from the station view, to inspect individual variables of each of the three entities. The variable view shows variable metadata attributes and their distributions. ManuKnowVis evolved iteratively in close cooperation with *providers* and *consumers* from the BMW Group. The success of our design is shown in a case study, where we outline different success scenarios and how it helped in externalizing and comprehending complex manufacturing knowledge.

There are several avenues for our research. One is to investigate the flow of parts through an assembly line to identify bottlenecks or to trace back errors and the resulting challenges for future visualizations. A second challenge is to evaluate how additional manufacturing entities, such as plants, can be added to the visualization interfaces of ManuKnowVis. Finally, the generalizability of our visualization concept should be investigated in other application domains.

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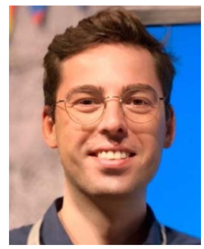

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