BIG DATA AND THE DATA VALUE CHAIN: TRANSLATING INSIGHTS FROM BUSINESS ANALYTICS INTO ACTIONABLE RESULTS – THE CASE OF UNIT LOAD DEVICE (ULD) MANAGEMENT IN THE AIR CARGO INDUSTRY

Research in Progress

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Abstract

Business intelligence and analytics enjoy a great deal of attention today. However, there is a lack of studies considering the full data value chain from (raw) data through business analytics to valuable decisions, i.e. also scrutinizing the latter stages of the data value chain, namely timely deployment and operational usage of valuable insights as demanded by practice. Following a design science approach, we develop a concept for the fast and flexible integration of valuable insights into daily decision support. A key feature of our concept is to provide valuable insights from business intelligence in an understandable manner to decision makers using a rule-based expert systems approach. In order to demonstrate the feasibility of our concept, we implemented a prototype in a complex real-world scenario, i.e. unit load device (ULD) management in the air cargo industry. This research in progress presents our preliminary findings and outlines the potential of the proposed concept.

Keywords: business analytics, data value chain, expert system, decision support, air cargo networks, ULD management

1 Introduction

The exploration of large and rapidly growing datasets and the exploitation of valuable insights are hot research topics today, including in information systems research (Agarwal and Dhar, 2014; Goes, 2014; McAfee and Brynjolfsson, 2012). Insights can be generated from (internal and external) data using business intelligence and analytics methods to improve decision support, e.g. in sales, marketing, and supply chain management (Kohavi et al., 2002; Trkman et al., 2010; Waller and Fawcett, 2013). Furthermore, this enables firms to optimise their business and to leverage more value from their data (LaValle et al., 2011), and also means that companies using data analysis for their decision making perform better regarding productivity and asset utilisation (Brynjolfsson et al., 2011; McAfee and Brynjolfsson, 2012).

Big data, its *data value chain*, and the promising *big impact* for business enjoy a great deal of attention in both practice and academia (Chen et al., 2012; Manyika et al., 2011; Miller and Mork, 2013; Sharma et al., 2014). While research in this domain examines the application and improvements of tools, methods, and technologies to discover valuable insights, e.g. trends and patterns (Manyika et al., 2011), practitioners demand its rapid utilisation (Finch et al., 2014). There is a lack of studies considering the deployment and operational usage of valuable insights, i.e. actionable results. Thus, knowledge is not enough and we must apply these derived insights to create value.

In our approach we take a look at common data mining process models (e.g. CRISP-DM, SEMMA and KDD). While SEMMA concentrates, in general, on data mining projects and neglects business aspects completely, CRISP-DM and KDD include a practical phase of deployment and knowledge integration (Azevedo and Santos, 2008). In the deployment phase of the CRISP-DM the customer needs to understand the actions that must be carried out by the models (Shearer, 2000; Wirth and Hipp, 2000). Thus, the results need to be integrated in processes and systems, e.g. identifying potential responding customers for promotions, but on the flip side a process and system requiring too much time and effort for utilising the relevant information would instead lead to unnecessary expenditures (Kohavi et al., 2002). Reaping the benefits of data analytics activities requires a transformation in valuable actions or decisions (Shanks et al., 2010). Especially in fast-changing environments, identified trends and patterns need to be used in a rapid manner, which leads to the need for reducing the time to generate value from derived insights (LaValle et al., 2011), namely: the time between knowledge retrieval and knowledge exploitation.

Since the first expert system was developed in the 1960s (Lindsay et al., 1993), and despite its age, expert systems are still a current subject of research (Liao, 2003, 2005) as well as in the area of supply chain management (Gunasekaran and Ngai, 2014; Waller and Fawcett, 2013). An expert system is able to reflect portions of human experts' thought processes in a specific domain and is well suited for supporting repetitive and structured decisions, processes and tasks in a narrow domain (Bobrow et al., 1986; O′Leary, 2007; Turban and Watkins, 1986) by applying knowledge, e.g. IF-THEN rules (Giarratano and Riley, 2005). Typical applications for an expert system that is able to support the decision maker by providing supplementary judgment and explanations (Turban and Watkins, 1986) are the diagnosis, interpretation of data, prediction, and control (Giarratano and Riley, 2005).

This paper emerged from joint work with a large logistics service provider for unit load device (ULD) management in the air cargo industry. Within the scope of the project, we faced the task of developing a system supporting daily business operations. Searching for a solution for the stated problems, namely the timely integration and provisioning of (new) information (e.g. from analytics activities) in an understandable manner to the end-user for decision support. We identified two approaches complementing each other: a combination of rule-based expert systems and business analytics activities. The symbiosis of these approaches enables us to provide valuable information from heterogeneous data sources to the end-user: respectively, the individual decision maker.

The objective of this research in progress is to: (a) present a system concept that contributes to the scrutiny, in particular, of the integration of derived insights, (b) implement and deploy the system concept to fairly complex real-world problem settings (i.e. data-intense ULD management in the air cargo industry), and (c) provide initial validation of the proposed approach and document findings.

Because of the engineering nature of our research, our work follows the design science approach that aims to solve identified practical organisational problems by creating and evaluating IT artefacts (Hevner et al., 2004; March and Smith, 1995). In particular, we base our work on the design science research (DSR) methodology for information systems research (Peffers et al., 2007) that is divided into the following process steps: (1) problem identification and motivation, (2) definition of the objectives of a solution, (3) design and development, (4) demonstration, (5) evaluation, and (6) communication.

According to Iivari (2015), we follow a strategy that attempts to solve a client's specific problem and construct an artefact from this experience to create a more general solution addressing the problem class, which can also be used for similar applications in other domains (Baskerville et al., 2009; Sein et al., 2011). Therefore, our paper is set out as follows: After this introduction (problem identification and objectives), we give a brief overview of the practical case in the context of ULD management in the air cargo industry. In Section 3, we present our proposed system design for an expert system-based decision support system (design and development). Section 4 demonstrates an implemented prototype and discusses our evaluation approach as well as first results (demonstration and evaluation). Finally, the paper concludes with a summary of the results and an outlook on the next steps (Section 6). The last step (communication) of the applied DSR methodology is realised by presenting the project results in the form of this article.

2 Data Analytics in ULD Management Business

Business intelligence and analytics seem a reasonable approach in response to competitive pressure and corporate growth (Chen et al., 2012; Manyika et al., 2011). This is certainly also true for the air cargo industry, which seeks constant improvement in operational business and a rational basis for decisions.

At the core of information-intense ULD management is the adequate provisioning of containers and pallets to customers (airlines). Our partner company runs one of the largest container fleets in the world and uses a very complex logistics network to provide containers and pallets to their customers worldwide. In order to achieve these objectives, the company employs over 70 experts including ULD dispatchers, implements several internal management information systems, and experiments with radio frequency identification (RFID) technologies to organise ULD allocation worldwide. Daily business operations consist, among others, of allocating empty serviceable ULDs between airports, relocating damaged ULDs to repair shops, and managing missing or lost units within the ULD network.

In an ideal world the air cargo network would exist without any uncertainties and risks (e.g. delays or cancellations) and every information and decision option would be known. However, obviously none of these circumstances are actually given. Temporary increases in demands for ULDs can appear if customers get additional business, like the Beaujolais event when a large number of containers were in demand for the worldwide delivery of red wine (Koch and Kraus, 2007). Aside from customer-specific network configurations and beyond regular and foreseeable events (which can be planned for accordingly), the system as a whole tends to be highly erratic, i.e. stochastic. To name a few examples, short-term weather conditions, strikes, and even handling times at airports can influence the feasibility of instructed ULD movements.

These characteristics, i.e. thought complexities of the system, make it hard to model the entire network and all relevant inputs in a complete, flexible, and still fairly comprehensible manner for any stakeholder. Nevertheless, the decision challenge for any ULD dispatcher remains, which is to derive valid if not optimal decisions. For example, a typical decision in ULD management is to determine which type and how many ULDs have to be requested and moved from a specific airport location to another in ULD demand. The more operational side of ULD management itself is embedded in traditional economic rationale, which would mean running a ULD business in the most efficient way possible.

Aside from historical master data, our partner company collected over 17 billion data records to track the full life cycle of every ULD in detail over the last decade. To give a rough estimate for the data volume recorded by the tracking engine each day: assume 3,500 flights a day, 10 ULDs per flight and only 3 event types (e.g. loading, flying, and unloading). In this case the daily data is comprised of 105,000 events. Furthermore, there are also transit flights, events associated with third party carriers, and many more event types to be considered. Aside from the internal data, ULD dispatchers are integrating external data sources in their decision-making process to understand the influence factors and try to handle the dynamic network.

At this point analytics comes into play. The huge amount of data in the company's data warehouse in combination with external data stores are ideally suited to identify patterns and relevant trends to better understand the network's peculiarities. The aggregation of such a flood of new complex information has to be managed and requires supporting tools to maintain the overview and make valuable decisions. Therefore, the visualization and exploitation of results is by no surprise a focal topic within data analytics (Gopalkrishnan et al., 2012; LaValle et al., 2011). To use these insights in an appropriate manner, we selected an expert system approach as a vehicle to transport this knowledge for decision support to the operating employees and support the handling of the network's complexity.

3 Design and Development of an Information System Capable of Coping with Data, Domain, and Decision Complexities

3.1 Designing the System

After implementing a proof of the concept system to assess the expert system technology as a promising approach for our case at an early stage of the project, we then evaluated its feasibility in several team meetings and workshops, and thus created the proposed system concept as a potential framework to cope with the given challenges.

Furthermore, we learned from previous iterations that such systems should provide: (1) flexibility with regard to the expansion and integration of data sources (internal and external), (2) support for rapid integration of new knowledge and its exploitation, (3) flexibility with respect to existing and changing business rules, strategies and objectives, (4) functionalities to communicate derived knowledge in an understandable manner to end-users, and (5) monitoring and control functionalities.

A key principle in the design process was to start small but grow with upcoming requirements, thus fitting the system to the need of the problem and not the other way around. A second principle was early stakeholder integration in order to receive feedback as soon as possible.

3.2 The System Concept

Figure 1 illustrates a high-level overview of our proposed concept. We divided the system into four layers, which we outline in this section: data sources, data preparation, expert systems, and consumers.

Data sources

Several daily decision tasks are highly dependent on internal and external data. Furthermore, it is often the case that the latest data is interpreted and used in conjunction with historical data. Also, we learned that, besides internal information from their own information systems, decision makers resort to external data sources that are located outside the company boundaries. Thus, our system concept considers: (1) both internal and external (raw) data, and (2) historical data and real time data. Internal data sources are defined as data storage that is located inside the company's boundaries and is owned by the company, whereas external data storage is located outside the company's boundaries. External data sources can be both free and commercial sources, like public Web services or commercial data providers. In addition, the system is not limited to structured and linked data (e.g. flights and airlines; flights and airports), but also unconnected data (e. g. weather or news feeds and airports or airlines), that become linked within the expert systems through the data preparers.

Data preparation

Central to our proposed concept is the idea to use (raw) data sources for ex-post and real-time data analysis for deriving patterns and trends to be built into an expert system for decision-making support. From our point of view it is not necessary to understand all available data sources and leverage the big data as a whole, but rather developing ideas, concepts, and prototypes stepwise to leverage the insights to value from the most important, most promising, or well-understood data sources.

In our concept, we see a data preparer as a module that has its own specialised task and supplies information as an outcome. Thus, such a module can be the result of a business analytics activity, for example the data pre-processing and application of a demand forecast model for containers that is constructed from historical data and applied to real-time data. The data preparers are responsible for the accurate processing and delivering of information at the time of requests. Locating the data preparers (logically and/or physically) outside the expert system aims to reduce the dependence on its availability.

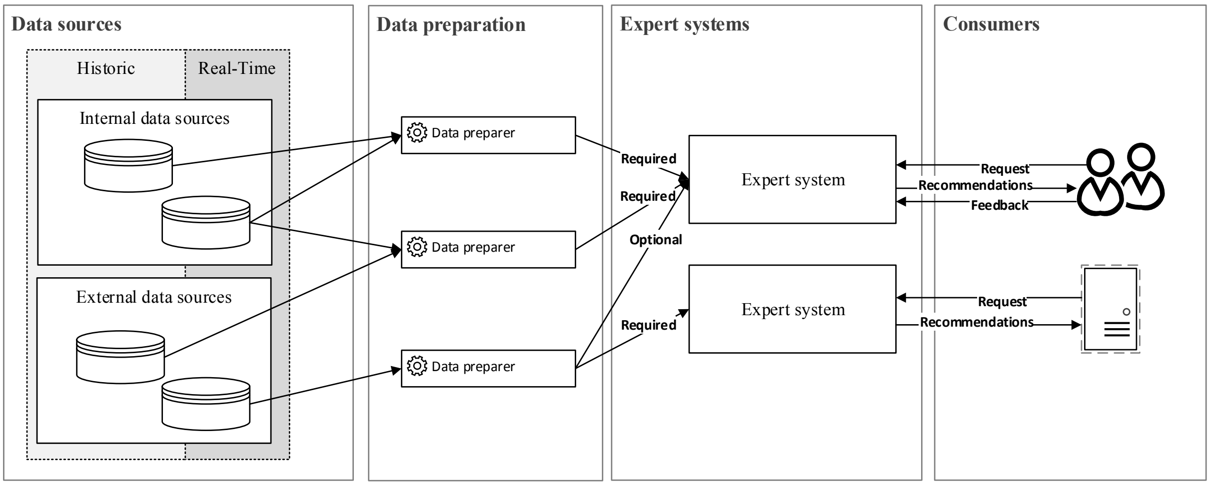

Figure 1. Proposed system concept on a high-level.

Our concept allows flexible module management – i.e. adding new modules and knowledge, respectively removing out-dated or incorrect ones – even during the runtime. Also, it allows the activation of data preparers on demand, but also easy deactivation if these are not needed or the information insights are no longer valid.

In addition, we design data preparers as required or optionally for a single expert system. Since the expert systems can only take available information into account, required data preparers have to be available when the expert systems generate recommendations. Optional data preparers are not necessary for creating recommendations, but can increase decision support quality.

Expert systems

As key elements in our proposed concept, (rule-based) expert systems are responsible for requesting and combining data streams from the data preparers with the knowledge about consumption.

The typical architecture of a rule-based expert system has the following components: A *knowledge base* that contains information to solve a problem, e.g. in the form of rules that are easy to understand for humans and a popular way to represent the knowledge (Waterman, 1986); a *fact base* that contains domain-specific data; an *inference engine* that matches and links both knowledge and facts; an *explanation facility* that justifies the solutions and enables the system to provide suggestions and explanations (Turban et al., 2005); an *user interface* that provides interaction functionalities to end-users; and a *knowledge acquisition* component that supports the maintenance and extension of the knowledge base.

While some decision-support systems generate reports for the user or the user is responsible for an appropriate representation, an advantage of using an expert system is its capability of explaining the generated recommendations (Giarratano and Riley, 2005). We opted for the expert system approach to relay the results and value directly to the operational users of the system via the user interface component. This allows us not only to use the insights, but also to provide a way to communicate and explain insights to the end-user. Since people are involved in the decision-making process, this will help them understand the presented solutions and to build trust and confidence with regards to the system. In our concept, the expert system's knowledge bases provide a way to conserve the knowledge as to how to use the insights and can function as documentation of the exploitation of insights in an easily understandable way. During the generation of recommendations the expert system requests the information from all known and connected modules and provides decision support based on the information and the knowledge about usage (i.e. rules). To limit the scope of the system, it is not designed to find the only correct solution or to run automatically. Its aim is to provide decision support based on all relevant and available information for the given decision problem.

An example of the knowledge acquisition process would be: After identifying useful information in the data a module is created that provides this information on demand, e.g. applying a weather forecast model on real-time data. In addition, rules are created, e.g. a rule that represents the prohibition of placing empty containers on an airfield when a certain wind speed is reached or anticipated. The expert system is able to use such knowledge in combinations to identify risky container supplies in advance. Another example is the low-pressure system *Xaver* which forced the airport in Hamburg, one of Germany's main export hubs, to cancel departures at the beginning of December 2013 (Brautlecht and Jefferson, 2013). Such rules enable the expert system to discard recommendations that are probably not possible or mark them as risky. In a leveraged perspective, any sensor along with business logic may be the source for real-time derived, new or temporarily valid facts for further new or temporarily valid rules.

The flexible management of modules and rules allows for the rapid development and testing of new expert systems without disturbing the existing infrastructure. Furthermore, the modular character of the system enables the flexible orchestration of the same data preparers, i.e. having separate expert systems for supporting ULD allocation, sales, or procurement support.

Statistics regarding created recommendations and used rules should be saved for later analysis. These enable the identification of new, out-dated, invalid or inefficient rules in the expert system's knowledge bases or information, improve the quality of the expert system, and satisfy the need for controlling and monitoring.

Consumers

Consumers can be individuals who request recommendations via an interface, like a website, but also machines that use the outcome for further processing. The task is to present generated recommendations with explanations to consumers in an efficient way to support their operations without additional effort. Further, it should be ensured that the system provides functionalities to receive feedback from consumers concerning recommendations for further improvement.

4 Demonstrating and Evaluating the System Concept in a Real-World Scenario

Parts of the proposed concept have been implemented in the form of a prototype. In this section, we present this prototype as well as our activities to validate the functionality of our concept. As described earlier, a core task in ULD management is the provisioning of ULDs. Thus, we apply concepts to support this task. The prototype's task is to integrate all required, relevant and available information and knowledge for appropriate decision support.

4.1 Applying the Proposed System Concept

Already using real-time data and information from the analysis of historical data, the prototype detects needs of action, creates recommendations with explanations, evaluates the alternatives according to rational and transparent criteria, and provides these options to the ULD dispatchers. Table 1 gives an overview of the implemented parts thus far. The prototype is implemented in Java 8 programming language in combination with the rule engine JBoss Drools. The expert system provides a web frontend as well as a REST API to provide recommendations and allows smooth integration into existing information systems and processes (Richardson and Ruby, 2007; Webber et al., 2010). Our prototype is already integrated into the existing systems and provides decision support on real-time data during the daily workflow routines of the dispatchers.

Consumers	Expert systems	Data preparation	Data sources
Web-interface for ULD dispatchers	Expert system for ULD allocation tasks	Weather information (Optional)	Weather Information Provider *Real-time external data*
		Flight events (Required)	Company's Database Server *Real-time internal data*
REST API		Stock details (Required)	Company's Database Server *Real-time internal data*
		Airport categorization (Required)	Company's Data-Warehouse *Historical internal data*

Table 1. Implemented modules in the prototype.

A more detailed description of every implemented component is beyond the scope of this paper; Figure 2 provides a snapshot of the Web-based frontend of the system as an example of its implementation.

The snapshot shows a situation in which the system identifies an understock of ULD containers at the considered airport and recommends solutions with explanations. As can be seen, the interface was implemented as user friendly and as simple as possible, i.e. it only provides as much information as needed on the first view, but offers the possibility of diving deeper by providing explanations like to retrieve information about airport characteristics and weather conditions.

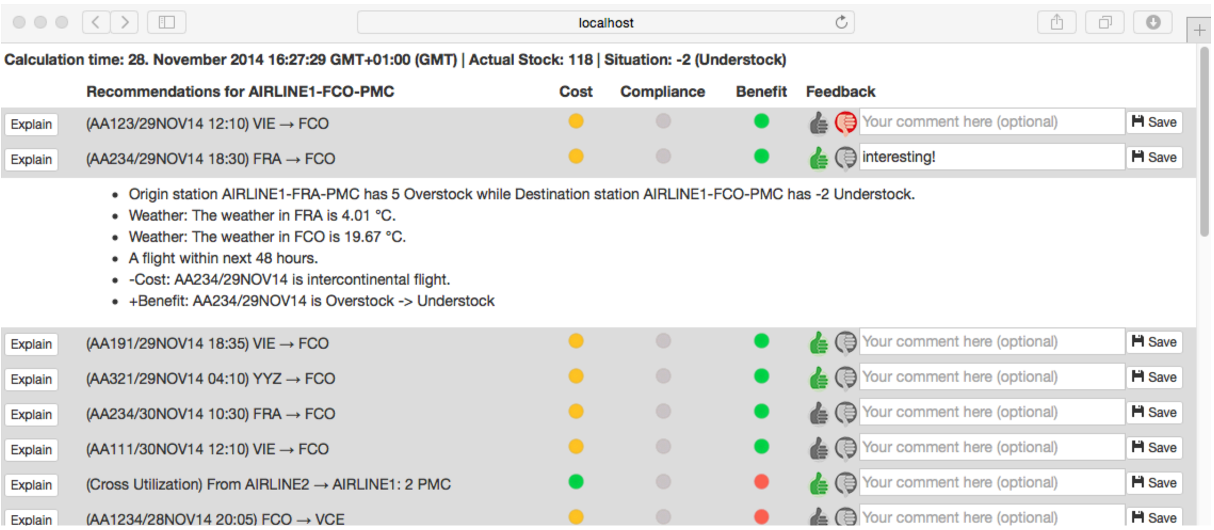

Figure 2. Snapshot of the implemented prototype's user interface.

We implemented a valuation method that provides a rationale besides the explanations: costs, compliance, and benefit. Furthermore, the screenshot shows that we implemented functionalities in the user interface that encourage the end-users to provide us with feedback (in the form of comments and likes) about technical issues, mistakes, or suggestions for improvement. We document and save the recommendations, which allow us to backtrack recommendations to rules and information (modules) used in order to enhance quality, identify any shortcomings, and record statistics for evaluation purposes.

4.2 Evaluation Activities and Preliminary Results

Evaluation is one necessary step in DSR (Gregor and Hevner, 2013). It aims to provide evidence about the effectiveness and efficiency of the designed artefact with regard to its objectives (Gregor and Hevner, 2013; Hevner et al., 2004; Peffers et al., 2007; Pries-Heje et al., 2008). Furthermore, the evaluation can also help to enhance the artefact design by achieving a profound understanding of the problem and the artefact's contribution to its solution (Markus et al., 2002; Muntermann, 2009; Sein et al., 2011). We carry out the evaluation in two ways, calculating performance indicators and collecting personal feedback from end-users.

Providing evidence that the system is capable of supporting and improving decision making we: (1) calculate performance indicators comparing real decisions performed by the dispatchers and the generated recommendations by the expert system, and (2) compare the top-rated recommendations regarding our defined criteria, i.e. cost, benefit, and compliance, with decisions made by human experts, to draw further conclusions regarding the system's contribution to rational decision making.

At this point the system is able to recommend and explain on average three quarters of real performed actions and reveals unexploited potential in daily decisions. Considering the system's task and its early prototype status, this is reasonable and provides evidence about supporting potential.

Currently, we are doing the first field tests of the prototype and collecting feedback from end-users about the system's outcome and usability. The feedback so far has been positive and useful for necessary system refinements, and confirms that the users understand and agree on the system's contribution.

In addition, we plan to evaluate the system as to whether or not it enables the exploitation of insights and thus the improvement of decision making and its quality (e.g. problem identification speed, decision speed, decision-making satisfaction) (Leidner and Elam, 1993; Lilien et al., 2004; Sanders and Courtney, 1985).

In order to quantify the rapid and flexible integration and provisioning of new insights, we will evaluate the timeliness in terms of time and effort for the system to integrate new information for decision support, i.e. the time between knowledge retrieval and knowledge exploitation, and an analysis of the monetary value of decisions in two scenarios: (1) having the new information for decision support integrated, and (2) not having the new information utilized.

Further evaluation needs to be conducted to demonstrate that the concept and its prototypical instantiation address the given problem, e.g. by stressing the system's functionality with respect to flexibility and robustness of information consumption, its communication capability to transport valuable insights, and its adoptability to shifting business environments.

5 Summary and Outlook

In this research in progress, we presented a system concept that copes with the challenge to act on insights from business analytics activities in the quickest way possible. We identified that such systems should provide: (1) flexibility with regard to expansion and integration of data sources (internal and external), (2) support for rapid integration of new knowledge and its exploitation, (3) flexibility with respect to existing and changing business rules, strategies and objectives, (4) functionalities to communicate derived knowledge in an understandable manner to users, and (5) monitoring and control functionalities. To the best of our knowledge, at least in the air cargo industry this is the first work that investigates the usage of rule-based expert systems for relaying insights from business analytics activities to the decision maker and addresses the problem at hand.

We demonstrated the application of our proposed concept by implementing and deploying a prototype in an extensive real-world scenario in the air cargo industry. Although the functionality of the system is still rather limited, the initial feedback was positive, constructive, and motivates further research in this direction.

Our working prototype will be used as a foundation for further refinements. We are confident that extending the data sources, adding further data preparers, enriching the facts and the rule base will improve its decision support quality and provide profound insights into the problem and the solution design. Furthermore, aside from some control measures, we will continue evaluation activities to provide further evidence of the utility of our proposed system concept and discuss its transferability to other scenarios.

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