Exploring Design Principles for Human-Machine Symbiosis: Insights from Constructing an Air Transportation Logistics Artifact

Completed Research Paper

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Abstract

This paper reports the findings of a proactive design science research project involving the construction, evaluation, and organizational introduction of an information technology (IT) artifact in the context of air transportation logistics. Drawing on our insights from instantiating an IT artifact and embedding it into the organization of a major provider of unit load device management for airlines, we explore the idea that IS-driven automation in digitalizing environments is more limited by socio-economic factors than digital-technological capabilities. Both our IT artifact and the abstracted design principles we generated through heuristic theorizing (HT) are novel, enhancing the information system (IS) design knowledge base of human-machine symbiosis and IT artifacts. Overall, our findings contribute to a better understanding of how to design human-machine symbiosis in information systems.

Keywords: human-machine symbiosis, air transportation logistics, design science research, heuristic theorizing

Introduction

The societal process of digitalization by which digital technologies are woven into the fabric of our everyday artifacts and life (Tilson et al. 2010; Yoo 2010) offers enormous business opportunities. One important consequence of digitalization is the exponential increase in data generation and availability (i.e., in terms of volume, variety, and velocity), which creates new opportunities for data analytics, algorithms, and ultimately decision-making support or automation (Agarwal and Dhar 2014; Goes 2014; Markus 2015; McAfee and Brynjolfsson 2012). Reaping the potential benefits from this new wave of IS automation (Zuboff 2015), however, entails significant challenges.

One key challenge of leveraging new IS automation potentials that arise in the context of digitalizing environments is identifying the appropriate level of automation given the contextual decision-making requirements (Mertens and Barbian 2015). IS automation theory identifies different levels of automation ranging from fully manual operations to computer use while preserving humans' full decision-making responsibility and up to full automation, whereby the computer acts autonomously (Bravo 2015; Bravo et al. 2016; Vagia et al. 2016). Depending on the specific context and requirements (i.e., economic, social, and technological), the level of automation that is desirable, feasible, and adequate overall varies. Thus, a key concern is purposeful IS automation and finding the appropriate level of automation given the specific context and requirements of the decision-making problem.

Situating our work in the socio-technical systems (STS) tradition, according to which information systems should be designed based on humanistic principles to improve work conditions and job performance, the concern for purposeful IS automation addresses the demand for intertwining the technical and social subsystems of work organizations based on the idea of joint optimization, that is, ensuring that these two parts interact to yield positive outcomes within an organizational context (Appelbaum 1997; Bostrom and Heinen 1977; McKay et al. 2012; Mumford 1983, 2006; Trist 1981; Winter et al. 2014). Previous research has suggested principles such as responsible autonomy, adaptability, meaningfulness of tasks, and feedback loops for designing work according to this notion of joint optimization (Maio and Paola 2014). Furthermore, to address the need for designing IT artifacts according to work satisfaction and similar social/organizational goals, prior research in the STS tradition has proposed principles for participatory methods of developing information systems to ensure alignment of IT artifacts with the concerns and work conditions of organizational users (Baxter and Sommerville 2011; Mumford and Weir 1979). Little research, however, has focused on design principles for constructing IT artifacts that embody the notion of joint optimization (Sarker et al. 2013) and address the concern for purposeful IS automation. In this paper, we address this gap in the literature through the overarching idea of human-machine symbiosis in building an IT artifact and associated abstracted design knowledge in the form of design principles (level 1 and level 2 contributions according to Gregor and Hevner 2013).

We conducted a multiyear design science research (DSR) project with the goal of simultaneously (a) constructing an innovative information technology (IT) artifact to address a specific IS automation problem and (b) building abstracted design knowledge to contribute to the IS automation knowledge base (Gregor and Hevner 2013; Gregory and Muntermann 2014). For this project, we engaged a major service provider of unit load device (ULD) management for airlines. In collaboration with our industry partner, our project involved constructing, evaluating, and introducing into an organization an IT artifact for improving the continuous utilization and allocation of ULDs in response to the fluid demand of airlines for air transportation logistics services.

Abstracting from our problem-solving experiences and the insights generated to the level of design knowledge (Baskerville et al. 2015; Gregor and Hevner 2013), this paper aims to contribute to our nascent understanding of how to achieve a symbiosis between human and machine for purposeful IS automation. Specifically, we develop a set of design principles for achieving human-machine symbiosis in IS design. We suggest that this set of design principles is particularly relevant when full IS automation is not feasible or desirable, for example, due to regulatory factors (Simon 1977). Our design principles contribute to our understanding of augmentation of humans through partial IS automation that considers humans and machines from a bilateral relationship perspective. We present an instantiation and evaluation of our set of design principles and discuss the missing components of an IS design theory (Gregor and Jones 2007).

This paper is structured as follows. After this introduction, Section 2 provides background knowledge on the problem context (digitalizing environments), the problem class (IS automation), and the proposed solution concept (human-machine symbiosis). Section 3 explains our research process and methodology. Section 4 provides background knowledge about our concrete problem and problem-solving environment. Section 5 details the heuristic search and theorizing process for the generation of our (nascent) design theory. Section 6 presents the outcomes of the evaluation of our IT artifact. Section 7 discusses and integrates our findings, and we conclude this study in Section 8, which includes an outlook on future research.

Theoretical Background

Digitalizing Environments

Digitalization, the societal process by which digital technologies become increasingly embedded into everyday life (Tilson et al. 2010; Yoo 2010), has changed the role and impact of IT in our world. Until about a decade ago, IT was considered primarily as a resource owned and controlled by individual companies (Bharadwaj 2000; Melville et al. 2004). Digitalization, however, has initiated a historic shift toward IT as an integral factor of companies' environments. In this vain, Tilson et al. (2010) refer to digital infrastructures as a new class of IT artifacts and Yoo (2010) makes the key observation that our everyday interactions are mediated through digital technology.

Digitalization and the consequent shift explained above have led scholars of IS history to identify a new era referred to as ubiquitous computing (Niederman et al. 2016), consumerization (Gannon 2013), or simply the digital age (Bharadwaj et al. 2013). A key observation about today's digital age is the exponential increase in the number and type of connections of physical elements (people and things) to the Internet and systems more generally. As a result, the volume and variety of data generated about these elements and relations between them has also increased (Lycett 2013).

For example, in the air transportation logistics environment, advances in digital weather data and prediction technologies may spring up and be introduced into the environment by one set of actors outside the airline industry, which may in turn produce opportunities for airlines and air transportation logistics providers to establish new connections between systems and their input providers, leverage new external data streams, and enable more precise and targeted resource allocation and interactions between providers and airlines. This is but one example of leveraging advancements in big data, analytics, and machine technology for speedy adaptation to digitalizing environments (Chen et al. 2012; Chui et al. 2015; LaValle et al. 2011).

Considering decision making as a process by which data is transformed into action, digitalization provides new opportunities (Abbasi et al. 2016; Kohavi et al. 2002; Trkman et al. 2010; Waller and Fawcett 2013). Managers are thus compelled to reassess options available inside their organizations to use systems to support or even automate decision making (Sharma et al. 2014). As we know from previous research, such options arise from data analytics capabilities (prescriptive analytics in particular) and the associated development and use of algorithms (Markus 2015).

IS Automation

Theorizing about automation in organizations through the application of IT is an essential part of information systems research (Frank 1998). Information systems are, in general, designed to incorporate, among others, the roles of informating, augmenting, and automating (Iivari 2007; Zuboff 1985, 1988). While the first two aim to support human decision maker, automation denotes the replacement of human involvement, including even cognitive processes (Fast-Berglund et al. 2014).

The term automation was brought to public attention by Diebold (1952) to mean both automatic operation and the process of making things automatic. Our definition here is narrower: automation is "the full or partial replacement of a function previously carried out by the human operator" fully or in part (Parasuraman et al. 2000, p. 287). This implies that automation does not have to be all or nothing.

Automation does not mean replacing human intervention; quite the opposite. With advances in machine technology, humans are asked increasingly to interact with automation (machines) in complex systems (Sheridan and Parasuraman 2005). The benefits of automation will exceed labor savings; instead, machines amplify the value of expertise by increasing an individual's work capacity and freeing the human to focus on work of higher value (Chui et al. 2015). Thus, automation systems are designed to achieve the best fit for the capabilities, strengths, and weakness of both human and machine (Vagia et al. 2016).

On the one hand, bounded rationality – that is, "the limits upon the ability of human beings to adapt optimally, or even satisfactorily, to complex environments" (Simon 1991, p. 132) – and other factors (e.g., economic pressures) drive companies' decisions to introduce IS and automate an increasing share of the work required to translate data into actions, eventually resulting in full automation in some cases. This trend is underscored by the current enthusiasm for the topic of big data in our field and improved technological capabilities for exploiting rapidly growing and diversifying data streams in real time with the help of algorithms (Markus 2015). On the other hand, we see an increasing number of instances in which IS automation potentials and the available technological capabilities exceed desire, the degree of acceptance, and societal constraints. For example, in our context of ULD resource allocation decisions in the air transportation logistics environment, we realized through heuristic theorizing that humans should be vested with the authority to make the resource allocation decision because of, for instance, regulatory constraints.

Beyond the benefits from automated systems, such as reduced mental workload, the design of such systems entails challenges to be considered, including the loss of human expertise, complacency, or loss of adaptability (Endsley and Kaber 1999; Hoc 2000, 2001; Parasuraman and Manzey 2010). The literature on the "ironies of automation" (Bainbridge 1983; Baxter et al. 2012) also makes clear that thinking critically about what has been referred to as "blind automation" is indispensable. The emerging design issue is the selection of functions to be automated and the scope of this automation (which we refer to as the Level of Automation, or LoA) (Parasuraman et al. 2000).

The literature proposes taxonomies to determine appropriate LoA (e.g. Bainbridge 1983; Baxter et al. 2012; Chialastri 2012; Endsley and Kaber 1999; Kaber and Endsley 2004; Vagia et al. 2016) spanning from fully manual to full automation (Vagia et al. 2016). Table 1 presents an LoA taxonomy for decision making we used to structure the evolution of our artifact design. According to the taxonomy, at LoAs 1-5 the human operator is in charge of the decision-making process. At levels 6-10, the computer takes a more active role in executing decisions (Nof 2009), ultimately replacing human involvement.

Level	**Description**
1	(*fully manual*) The computer offers no assistance; the human must take all decisions and actions.
2	The computer offers a complete set of decision/action alternatives, or ...
3	narrows the selection down to a few, or ...
4	suggests one alternative, and ...
5	executes that suggestion if the human approves, or ...
6	allows the human a restricted time to veto the suggestion before automatic execution, or ...
7	executes the suggestion automatically, then informs the human, or ...
8	informs the human only if asked, or ...
9	informs the human only if it, the computer, decides to.
10	The computer decides everything and acts autonomously, ignoring the human. (*full automation*)

Table 1. Levels of Automation for Decision-Making (adapted from Parasuraman et al. 2000).

Human-Machine Symbiosis

The term symbiosis, coined in 1879 by plant pathologist Anton de Bary (de Bary 1879; Douglas 1994), describes the living together of different species in a beneficial (but also non-beneficial) relationship. The literature about the intelligent combination and symbiosis of humans and machines often labels such systems as joint cognitive systems, symbiotic decision support systems, intelligent decision support systems, and so on (cf. Dalal and Kasper 1994). While these concepts differ in a number of aspects, they share a fundamental tenet: overall, system performance can be improved significantly if humans and machines are viewed and evaluated as components of a joint system, and their individual actions are coordinated such that they contribute synergistically to a shared set of system goals.

The dominant perspective in past research is that machines are the assistants of humans to achieve humans' goals of automation, information, or augmentation (Iivari 2007). Automation of human operations is driven not only by economic reasons, but is also to be extended to tasks humans do not want to perform or cannot perform as accurately or reliably as machines. Thus, automation aims to reduce, to the extent possible, all human intervention, for example, to reduce human errors in the behavior of the system (Ekbia and Nardi 2014; Zuboff 1985); information refers to the capability to collect and generate information from the automation of tasks and activate the informating potentials of IT (Zuboff 1988); and augmentation refers to the idea that technology can amplify human cognition (Engelbart 1962) and help overcome the bounded rationality of humans (Simon 1991). There exists, however, an opposing view: that humans are the assistants of machines to achieve machines' goals. What these goals of (learning and increasingly intelligent) machines might be, precisely, has not yet been well studied. What we do know is that machines may start to take actions that were unintended by the original systems owner (e.g., some algorithmic trading machines have begun performing unexpected and uncontrolled actions in financial markets), akin to the generativity of digital infrastructure evolution. Taking this opposing view of the machine-human relationship, prior work on the concept of heteromation has described processes and examples (e.g., Amazon's Mechanical Turk) of integrating humans back into computational, machine-dominated systems (Ekbia and Nardi 2014).

In addition to theorizing the relationship between humans and machines, prior research has shed light on the factors that influence human-machine symbiosis. The dominant perspective in past research is that the distinct abilities and qualities of humans and machines, respectively, are the main drivers of human-machine design choices. Accordingly, "computing machines can do readily, well, and rapidly many things that are difficult or impossible for [human], and [humans] can do readily and well, though not rapidly, many things that are difficult or impossible for computers" (Licklider 1960, p. 6). The advent of more powerful artificially intelligent software and algorithmic power suggests that human actions can be, in many contexts, automated completely with the help of machines (Brynjolfsson and McAfee 2014; Zuboff 1985, 1988). Machines are said to be efficient in computing complex mathematical equations, carrying out automation tasks free of computational errors, and making better decisions than humans (Schalk 2008). However, machines are also said to be limited in their capabilities in that they lack intuition, feelings, and creativity. Further, in contrast to the human ability to operate in uncertain environments (Ferreira et al. 2014), machines are assumed to lack this ability because they cannot accurately predict and handle so-called black swan events (rare, unexpected events of large magnitude and consequences) or so-called coconut uncertainty (rare events with critical consequences), which researchers explain with the low, non-computable probabilities or their first-time occurrence in reality (Licklider 1960). In sum, prior research suggests that there are some tasks machines can perform more effectively than humans (i.e., precisely defined, mundane, and routine tasks), while there are others that humans do more effectively (i.e., tasks requiring intuition, creativity, and human senses). As a result, human-machine symbiosis is viewed to be driven by the motivation to combine the respective strengths (Ferreira et al. 2014).

Considering the division of labor between human and machine and its evolution, the literature distinguishes between static automation (once an LoA is defined, it remains fixed or static) and abilities that enable a change in the level and/or type of automation during systems operations. There is a variety of research about adaptive automation concepts (see Vagia et al. 2016). Most of the work on adaptive automation considers that the automation solution itself decides on the LoA. In our work, we refer to the concept of adaptable automation, in which the human operator remains in charge and decides how much automation will be used.

Methodology for Building Design Theory

Our methodology for building (nascent) design theory (Gregor and Hevner 2013; Gregor and Jones 2007) was informed and inspired by the origins of DSR in fields such as engineering and computer science, which are essentially problem-solving disciplines (Iivari 2007; Simon 1996). Based on this historical view of DSR as a research paradigm that combines problem solving with design theorizing, we draw on the recently proposed heuristic theorizing framework for proactive DSR (Gregory and Muntermann 2014; Iivari 2015). Accordingly, our goal was to create a new and innovative artifact that would extend the boundaries of human and organizational capabilities (Hevner et al. 2004) while simultaneously generating abstracted prescriptive design knowledge to guide future artifact construction activities in other instances of our identified problem class (Gregor and Hevner 2013; Gregor and Jones 2007).

In Iivari's (2015) typology of DSR strategies, our approach corresponds to Strategy 2, that is, proactive DSR, which is based on close researcher-practitioner relationships and begins with a specific problem faced by practitioners. To generate design theory within this proactive DSR variant, heuristic theorizing (HT) has been proposed, defined as "the process of proactively generating design theory for prescriptive purposes from problem-solving experiences and prior theory by constantly iterating between the search for a satisficing problem solution, i.e., heuristic search, and the synthesis of new information that is generated during heuristic search, i.e., heuristic synthesis" (Gregory and Muntermann 2014, p. 651). Our decision to opt for DSR, and in particular HT, was based on two points. First, our joint work aimed to design, implement and evaluate (establishing the proof of concept) an IT artifact. Second, the HT framework offers useful guidance for combining two strengths of DSR that are difficult to accommodate in practice: solving a problem in the researcher's environment through an innovative IT artifact and contributing to the knowledge base by theorizing about the problem class and solution design. In addition, it supports theorizing about IT artifacts and the ways in which they emerge and evolve over time and how they interact with socio-economic contexts (Orlikowski and Iacono 2001).

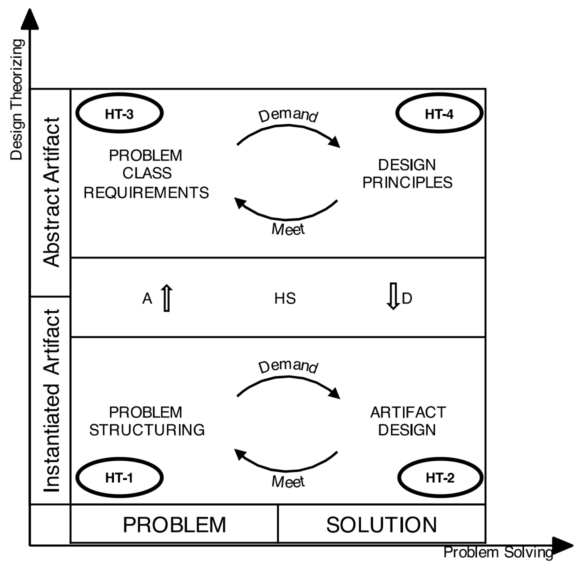

Figure 1. Heuristic theorizing framework (adapted from (Gregory and Muntermann 2014))

Accordingly, to account for design theorizing concerns, the framework in Figure 1 distinguishes between the level of abstraction: abstract/general artifact and situated/instantiated artifact in a specific context (see, also, the discussion about different levels of DSR contributions in (Gregor and Hevner 2013) and (Baskerville et al. 2015)). To account for problem-solving concerns, the framework also distinguishes between the problem and the solution. HT envisions a highly iterative research process in which the DSR team shifts between the different levels of abstraction (called abstracting (A) and de-abstracting (D) in HT) on the design theorizing dimension, and between the means/solution and ends/problem on the problem-solving dimension.

To guide the reader in the main part of our paper that follows (section 5), in which we present the evolution and outcomes of our heuristic theorizing process, we use the following abbreviations that appear in Figure 1: HT-1 indicates a period during our research process when we were engaged in structuring the problem at hand; HT-2 indicates a period during which we were working on the design of the instantiated IT artifact; HT-3 indicates a period spent theorizing about the abstract problem class; and HT-4 indicates a period in which we were theorizing about the abstracted design knowledge, in particular design principles (DP) and their underlying rationales.

We also present a final evaluation of the IT artifact resulting from the process of heuristic theorizing, which is in line with general guidelines for DSR (Gregor and Hevner 2013; Hevner et al. 2004). It aims to provide evidence about the effectiveness and efficiency of the designed solutions with regards to its objectives (Gregor and Hevner 2013; Hevner et al. 2004; Peffers et al. 2012; Pries-Heje et al. 2008). Furthermore, it can also help enhance the artifact design by achieving a profound understanding of the problem and the artifact's contribution to its solution (Markus et al. 2002; Muntermann 2009; Sein et al. 2011). In the course of our DSR project, we conducted several evaluation activities to ensure that the solution meets the demands of the problem (Venable et al. 2014). In addition, to provide evidence of the improvement potential of the symbiotic relationship, we provide quantitative measures in an *ex-post* evaluation (section 6).

For the empirical grounding of our design theorizing, we employed a multimethod design and collected both qualitative and quantitative data (Goldkuhl 2004). This approach is deemed suitable for explanatory and confirmatory purposes (Venkatesh et al. 2013). Through our close cooperation with our practice partner and because three of the authors have been involved directly in building and evaluating the prototype system throughout the requirement analysis, design, implementation, and introduction phases, we have access to a large amount of project material, in the form of working documents, presentations, email messages, meeting notes of design workshops, audio recordings of participant observations, focus group meetings, and so on. This allows us to consider a multiple stakeholder perspective (e.g., operations' view through ULD controllers and the COO, in addition to an IT perspective) on the problem and the emerging solution design. New findings during data analysis were structured by the university DSR team, and presented and verified in design workshops and conference calls. Table 4 in the Appendix provides an overview of our fieldwork.

ULD Resource Allocation in Air Transportation Logistics

We carried out DSR and engaged in heuristic theorizing with a logistics service provider of ULD management in air transportation logistics whose value proposition is to supply airlines with ULDs, that is, containers and pallets used for freight transportation (e.g., suitcases of passenger, cargo, or mail), and provide associated ULD management services. ULD-Provider (as we refer to the company we worked with from here on) uses a complex logistics network to provide its fleet of more than 90,000 uniquely identified ULDs (one of the world's largest) to customers globally. This fleet includes 98 different types of ULDs used for specific transportation purposes (e.g. perishables, textiles, valuables, vehicles, animals) and suitable for all aircraft types used by ULD-Provider's customers.

The main day-to-day operational challenge of ULD-Provider is to supply airlines across different airports with empty serviceable ULDs, but also to remove and repair damaged units and supply them back to the network in the most efficient and timely manner. The company conceived the idea to leverage available internal and external data streams better and improve ULD logistics with the help of big data and machine technology. ULD-Provider approached us (the university-based DSR team) in 2012 with this exact problem statement and asked us to collaborate in the joint development of a prototype and IT artifact to address the challenge it posed.

ULD-Provider has to determine continuously both the quantity and type of empty ULDs to order and move from one airport location to another depending on continuous changes in airline/customer demand and stochastic damage, missing and lost rates. To do so, it employs human ULD controllers with very specific domain knowledge who are responsible for efficient resource allocation of the company's worldwide ULD fleet (e.g., partitioned by geographic regions or customers). Daily operations consist of continuous monitoring of trigger scenarios to anticipate ULD demand, supply additional ULDs for unexpected transportation events (e.g., charter flights), or replenish stocks to decrease underutilized resources.

ULD controllers rely on information about the logistics network's current state retrieved from ULD-Provider's internal database and manually determine the need to replenish or recall stocks at an airport. They do so by selecting possible allocation alternatives without support of the machine, sending so-called movement orders to responsible on-site ground handling agents. These decisions depend on accurate and timely data. However, in most cases, ULD controllers cannot estimate whether reliably the movement order will be executed until the requested flight's departure and until they receive direct feedback about the execution from the operating facilities via the sending of event data. There is often a time lag between the logical state of the system (represented by data saved in the database) and the physical level of the on-site inventory.

To maintain its viability in the air transportation business and stay ahead of competition, a ULD company must carefully balance customer demand with optimal ULD supply to ensure the highest-possible efficiency of logistics. To this end, ULD-Provider could maintain high stock levels and slack resources at each airport, which would be highly inefficient and costly, or eliminate slack resources and ensure operational efficiency through a smart allocation of ULD stocks.

Heuristic Theorizing Process

In line with the iterative nature of DSR and with guideline #6 – design as a search process – suggested by (Hevner et al. 2004), this section provides a detailed description of our heuristic search and theorizing process (see Figure 1), referring to the levels of automation introduced earlier (Parasuraman et al. 2000). It is organized in chronological order beginning with initial problem understanding and the lowest level of automation, in which machines offer no assistance to ULD controllers, who take all decisions and actions manually (see Table 2: LoA-1), and concluding with our latest problem formulation and solution design. We ended up moving organizational decision making to the fifth LoA (see Table 2: LoA-5). We also derived a set of design principles. Due to space limitations, we focus the following narrative on the most important cycles, time periods during our research process, and outcomes.

Iteration 1: Knowledge-based Recommender Systems for ULD Resource Allocation in Air Transportation Logistics

Our research project began with a series of workshops with ULD-Provider. The status quo we encountered was that ULD resource allocation alternatives were identified manually and decisions by ULD controllers were not supported by machine intelligence. This relates to the lowest level of automation (see Table 2: LoA-1). Entering the heuristic theorizing process through structuring the problem at hand (see Figure 1: HT-1), we defined an initial set of requirements for the design of a new system aimed at leveraging digital technology to improve decision making regarding ULD resource allocation. One specific requirement we identified was that, considering the relevant logistics network from a holistic viewpoint, the system should identify airports with over- and understock situations and generate recommendations for resource allocation decisions taken by ULD controllers.

Based on this understanding of the specific problem, we shifted to artifact design (see Figure 1: HT-2). The first step in our prototype development was to analyze the “as-is” and model the “to-be” decision-making process of ULD resource allocation with the help of participatory observations and interviews with ULD controllers. From this process of data collection, analysis, and creation of a shared understanding between the design team and ULD-Provider, we derived a detailed flow chart. The use of this modeling heuristic was complemented by drawing on decision-making theory, that is, Simon’s extended decision-making phases (Simon 1977): intelligence, design, choice, and review. During the design process, we realized that by playing with this kernel theory we could provide more targeted support and automation for individual phases, for example, by means of business intelligence and analytics (Chen et al. 2012). Overall, the first step of artifact design in our case resulted in the design and formulation of the decision-making process to be embedded in the new system (see Figure 2).

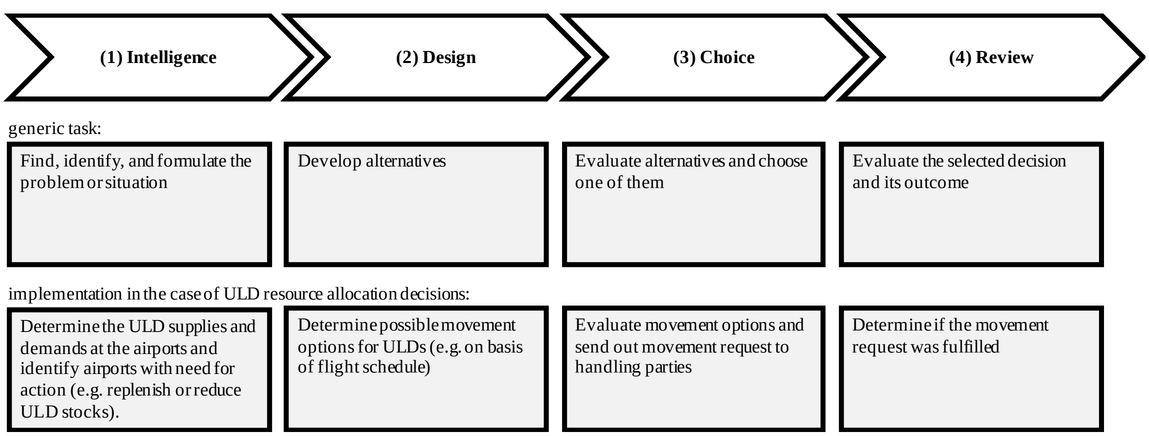

Figure 2. Decision-making phases in the case of ULD resource allocation

This initial iteration of problem structuring and artifact design offered fertile ground for the initial theorization of the meta-requirement to be addressed in general terms by the new system (see Figure 1: HT-3: abstracting from experience gained during HT-1 and HT-2): the need to determine and implement a *purposeful level of automation*. In particular, the research team and collaborators from ULD-Provider quickly realized there was potential to automate ULD resource allocation decision making at least partially by leveraging digital technology. However, an unresolved question that emerged from joint reflection was exactly how far to go with the use of digital technology in this type of decision-making context. The tension was expressed in a workshop protocol from December 2012: "The system should provide ULD controllers with suggestions for better allocation of ULD resources. However, at the end of the day the ULD controller should (freely) take the decision."

Continuing with artifact design (see Figure 1: HT-2), we played with the application of existing design knowledge and identified knowledge-based recommender systems (KBRS). This design choice allows for modeling the decision-making process as rules and considering information as facts. Drawing on KBRS guided further artifact design activities with ULD-Provider at this stage. In particular, this helped us address the meta-requirement mentioned above by avoiding full automation and emphasizing the supporting character of the system (see Exhibit 1).

> The primary purpose of recommender systems (also called recommender engines and advisory systems) is to help people make good choices and decisions in large and complex information spaces (Burke et al. 2011). They are known as intelligent decision support systems, which aim to address information overload problems and enhance human cognitive capabilities (Chen et al. 2013; Kaklauskas 2015). Various techniques for recommendation generation have been proposed to support users by finding items most suited to their interests; the most common types of recommender systems are collaborative, content-based, knowledge-based, and hybrid (Jannach et al. 2012). Knowledge-based recommender systems suggest items based on inference about users' needs and preferences.
>
> The recommender systems literature mentions rule-based expert systems as one possible technology to implement KBRS. The typical architecture of such systems includes an explanation facility to justify solutions and enable the system to provide suggestions and explanations (Turban et al. 2005). Expert systems differentiate between facts (domain-specific data, e.g., current station stock level) and knowledge (information to solve a problem), which can be represented in the form of "if-then" rules that are easy for humans to understand (Waterman 1986).

Exhibit 1. (Knowledge-based) recommender systems

Drawing on KBRS principles and guided by the decision-making model in Figure 2, we implemented a proof of concept as a standalone prototype (Prototype-1) in the Java programming language in combination with the rule engine JBoss Drools, which supports business process modeling (Red Hat, Inc. 2015). We defined the ULD controllers who are responsible for a problem or situation (see Figure 2: intelligence) as users of the KBRS and the movement alternatives (see Figure 2: design) as items. Prototype-1 provided functionalities to support and partially automate the intelligence and design phases (see Figure 2: intelligence & design), leaving ULD controllers, however, with full control over final resource allocation decisions (see Figure 2: choice). In particular, Prototype-1 was able to (1) detect the need for action at airport locations based on productive data, (2) create recommendations for ULD movements with explanations, (3) generate recommendations to ULD controllers, and (4) provide features to submit feedback. Prototype-1 was accessible through a web interface (see Figure 3). Furthermore, Prototype-1 was designed with consideration of existing IT systems at ULD-Provider that already supported the review phase (see Figure 2: review), with the idea of the new and old systems working in combination.

At this stage of our heuristic theorizing process, the initial ideas for three of our nascent design principles were generated (see Figure 1: HT-4). First, the artifact should align machine inference with human problem solving (see Table 3: DP-A – align). In particular, based on the rationale of human centeredness and the idea that machines primarily aid humans (see Kling and Star 1998), the design and implementation of Prototype-1 was guided by the previous analysis and mapping of the desired decision making and human problem-solving process. Second, drawing again on problem-solving activities conducted to this point as well as the rationale that users need to understand, appreciate, and buy into recommendations provided by the system to make best use of it, the artifact should provide human expert users with transparency about the generation of machine inference (see Table 3: DP-A – transparency). Third, based on the rationale of actively involving users in the continuous improvement of the system for better and more direct processing of user feedback, the idea emerged that the artifact should encourage human expert users to feed the machine with new information (facts and rules) (see Table 3: DP-H – feed). For example, user feedback involved information about missing movement alternatives or suggestions for considering additional data sources.

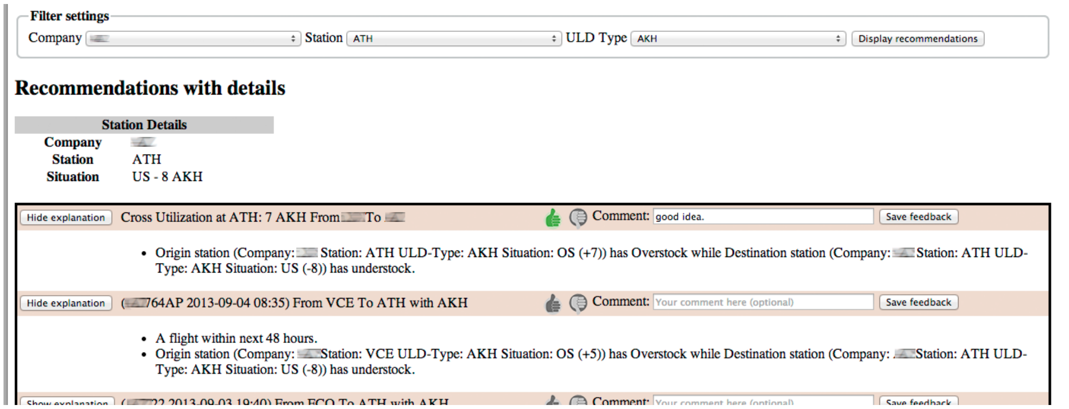

Figure 3. Screenshot of implemented Prototype-1's user interface

Reflecting upon the insights and outcomes of our heuristic theorizing process so far, we moved from the lowest level of automation to the next level, at which the system offers a set of recommendations for resource allocation to ULD controllers (see Table 1: from LoA-1 to LoA-2). During this reflection phase, we also realized that the taxonomy of 10 levels of automation (see Table 1) we had tentatively selected needed to be refined and adapted to our specific context of ULD resource allocation. This led to our revised taxonomy of five LoAs presented in Table 2.

The successful implementation of Prototype-1 triggered the first formative evaluation activities of our study, with the goal of exploring the usefulness of our tentative problem solution. We presented Prototype-1 to two ULD controllers and two members of ULD-Provider's IT department through a walkthrough using real historical data. We collected feedback through focus groups and interviews (see Table 4 in the Appendix for detailed information). The results confirmed the usefulness of the system, that recommendations made by the system were actually performed in specific situations, and that ULD controllers recognized themselves in the recommendations presented. The feedback also suggested, however, that the system still had shortcomings with respect to leveraging the full automation potentials provided by big data and associated technologies.

Extending our current problem formulation with the help of this new feedback, we shifted back to problem structuring (see Figure 1: HT-1). We made further observations of daily routines and identified additional internal and external data sources (e.g., weather or news ticker) that influence ULD logistics decision making. Based on new ideas of leveraging more real-time external data sources, we realized that the monolithic architecture of Prototype-1 did not provide sufficient flexibility. In further workshops with ULD controllers, we also learned that multiple stakeholders with diverse and somewhat contradictory goals influence ULD resource allocation. We agreed that the system should be able to reflect these aspects, consider different objectives, and align recommendations with defined business objectives and ULD-Provider's business model. In addition, we recognized that the system generated long lists of recommendations, thus exacerbating rather than solving the problem of information overload. Furthermore, we came to the point that we needed quantitative measures to monitor improvements of the system when adding new rules and facts.

After verifying with ULD-Provider in design workshops the usefulness of addressing these additional requirements, we shifted to artifact design (see Figure 1: HT-2) and incorporated the new ideas into our system design by implementing Prototype-2 as a modular service-oriented architecture (in contrast to the monolithic architecture in Prototype-1) (see Figure 4) (Döppner et al. 2015).

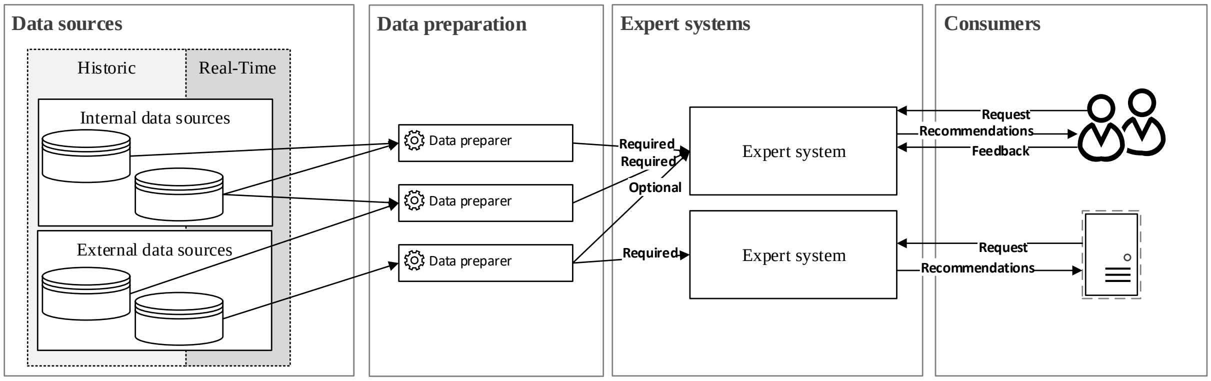

Figure 4. Prototype-2's system architecture at a high level

We conducted design workshops with different stakeholders from the company to define a set of criteria to score recommendation movement alternatives and sort them accordingly. The criteria were verified later with the rest of the project team, including stakeholders from Operations and Finance. Thus, in implementing Prototype-2, we addressed the information overload problem mentioned above and decided to score recommendations by defined criteria to help ULD controllers filter the list. Through joint interactions including workshops with ULD-Provider, we identified three criteria representing economic, operational, and value-creation perspectives: cost, compliance, and benefit. Consulting the literature, we adopted an approach from multi-criteria decision support systems focused on list-based ordering of identified recommendations (Adomavicius et al. 2011; Manouselis and Costopoulou 2007). We used the Simple Additive Weighting (SAW) method, also known as the Weighted Sum Method (WSM), which seeks to obtain a weighted sum of the performance rating of each alternative considering all attributes (Chou et al. 2008; Triantaphyllou and Sánchez 1997). According to these ideas, we incorporated new design features into our artifact solution (see Figure 1: HT-2).

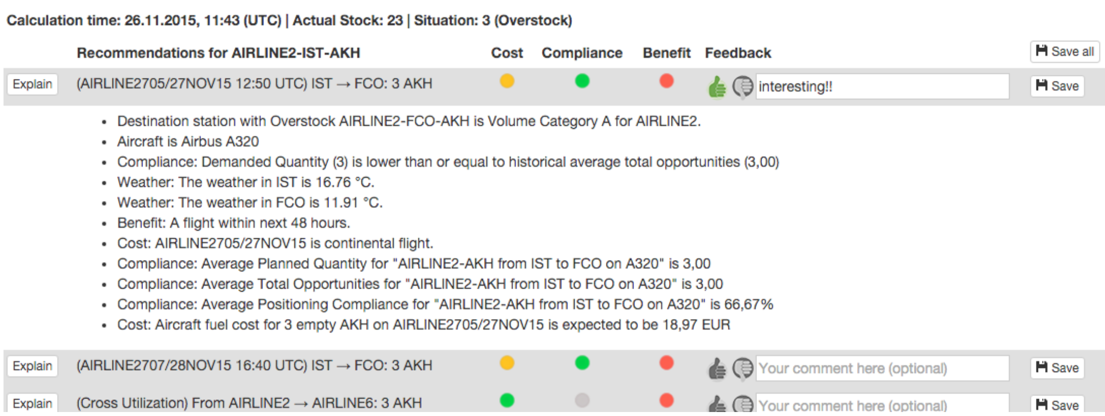

Figure 5. Snapshot of implemented Prototype-2's user interface

Figure 5 shows the user interface of Prototype-2 with (1) recommendations ordered by defined scoring function (represented by traffic lights) and displaying missing data (grey traffic lights) and (2) explanations enriched by external data, that is, inclusion of weather data and provisioning information about the feasibility and justification of single movement options. In contrast to Prototype-1, which was only loosely coupled, the enhanced system was technically integrated into the existing IT infrastructure of ULD-Provider. We adapted the graphical presentation to achieve a similar appearance to existing ULD-Provider web interfaces. Recommendations were now accessible as part of the daily work routines of ULD controllers.

Abstracting a second time from instantiated artifact design activities, the current set of design principles (DP-A – align, DP-A – transparency, DP-H – feed) were confirmed and remained stable. In addition, four new design principles emerged at this stage of heuristic theorizing. First, based on the rationale that the expert user needs to be given autonomy in the final decision of whether to adopt or disregard recommendations given by the machine, the artifact should provide human expert users with a level of confidence regarding suggested action alternatives (DP-A – level of confidence). Second, based on the rationale that the machine needs to be improved and adapt to new problem states in a timely and efficient fashion, and through the idea of being more informated through the automation by machine (Zuboff 1985), the artifact should enable the machine to identify and alert about missing knowledge autonomously (DP-H – alert). Third, based on the observation that ULD controllers tend to identify new sources that inform their daily decision making as well as the rationale that ongoing digitalization constantly generates new amounts and types of relevant business information to be considered for decision making, the artifact should be capable of continuous extension of the scope and variety of information processing (DP-S – continuous extension). Fourth, based on the rationale that machine capabilities need to embed smoothly into the day-to-day working and decision-making life of users, the artifact should reduce friction between human expert users and the machine (DP-S – reduce friction).

During qualitative evaluation of our revised instantiated IT artifact, we detected the need to provide evidence of the system's capability to augment human decision making and ULD logistics. Within the research team, we agreed on measures to calculate performance indicators of the human-machine cooperation comparing real movements instructed by ULD controllers and generated recommendations by the machine, thereby helping us to identify and present potential gaps in the system's knowledge base. With the introduction of Prototype-2, we shifted to a higher level of automation in which the machine suggests (ranked) alternatives (see Table 2: LoA-3).

Iteration 2: Human-Machine Symbiosis Decision-Support for ULD Resource Allocation in Air Transportation Logistics

We realized that full machine-based automation of ULD logistics was not feasible for regulatory reasons, despite technological opportunities. So, we shifted our focus in our second iteration from technical solutions and technological capabilities to a more socio-technical perspective and began to engage in the design of a symbiotic relationship between humans and machines to balance technological capabilities with social or regulatory concerns (see Figure 1: HT-3). Returning to the requirement that human agents in logistics systems should be an essential part of solving decision problems and a necessary part of system design, particularly in the air transportation logistics domain, we identified the idea of purposefully designing human's role in an increasingly machine-driven system.

De-abstracting to the level of instantiated artifact development, we reassessed Prototype-2 with ULD controllers from the perspective of interplay between social and technical subsystems in human-machine systems. Restructuring the problem at hand (see Figure 1: HT-1), we were prompted by feedback from ULD-Provider to emphasize the responsibility and accountability of humans in machine-dominated systems as final decision makers. Under certain circumstances, ULD controllers may hesitate to let the system automate and take over some of their tasks. However, if they viewed the machine and its recommendations as reliable, they might delegate some of their tasks to the machine to reduce their workload. This was also confirmed through verbal feedback after we presented the latest prototype's features in a *jour fixe* of ULD controllers and were asked for the implementation of a "just-do-it button." In particular, we received feedback from ULD controllers that the system should provide functionalities to prepare recommended alternatives for execution. Finally, in addition to existing performance measures (see Iteration-1), we identified the need for overall performance measurements with respect to the human-machine symbiosis.

Continuing with artifact design (see Figure 1: HT-2), we improved the explanation facility and developed Prototype-3, which (1) informs the ULD controllers if it is not able to collect enough information for recommendation generation and (2) detects knowledge (facts and rules) leading systematically to badly and unhelpfully rated recommendations (i.e., thumbs down by ULD controllers). We enhanced the system to quantify improvement of recommendations by introducing a quality measure enabling us to compare top-rated recommendations regarding our defined criteria (i.e., cost, benefit, and compliance) with decisions made by human experts and reveal unexploited potentials for better decision making. Prototype-3 introduces functionalities to create automatically (but not send) movement orders from recommendations (see Table 2: LoA-4) (see "Create MR" in Figure 6). Technically, the system is able to execute (create and send) movement orders (see Table 2: LoA-5), which is not yet activated.

Abstracting from the new problem-solving experiences during this second iteration of heuristic theorizing, we were able to once again confirm the current set of design principles. Once again, new design principles emerged. First, based on the rationale of a dynamic, reciprocal, and socio-material relationship between humans and machines as well as the idea that technology designs consider the evolutionary nature of artifacts and their environment context (Gill and Hevner 2013), the artifact should be adaptable to the current state of evolving human-machine relationship (DP-S – adaptable). In our case, the design and use of the emerging system over the various versions of our prototype evolved based on equal considerations of social and material perspectives, focusing both on what is possible technologically as well as what is done and desired socially and from a regulatory viewpoint. Second, based on the rationale of empowering the user organization and mitigating the risks of an overly normative designer's stance, the artifact should enable human expert users to configure the level of automation (DP-S – level of automation). In our case, it was deemed more appropriate to let ULD-Provider as the user organization take the final decision on the best level of automation, rather than letting the design team enforce their preference based on their view that was shaped heavily by what is now possible technologically. Finally, based on the rationale that both human and machine components of the overall decision making system exerted considerable influence over realized action trajectories, the artifact should provide holistic performance measurement of the system as a whole (the combination of human expert users and the machine) (DP-S –holistic performance measurement). The emergent data about the system's performance provide indications for shortcoming and further improvements (cf. informating in Zuboff 1985, 1988).

Level	Description
1	Machine offers no assistance; human must take all decisions and actions.
2	Machine offers a set of recommendations.
3	Machine suggests (ranked) recommendations.
4	Machine prepares recommendation for execution if the human approves.
5	Machine executes recommendation if the human approves.

Table 2. LoAs for Human-Machine Symbiosis for ULD Resource Allocation in Air Transportation Logistics

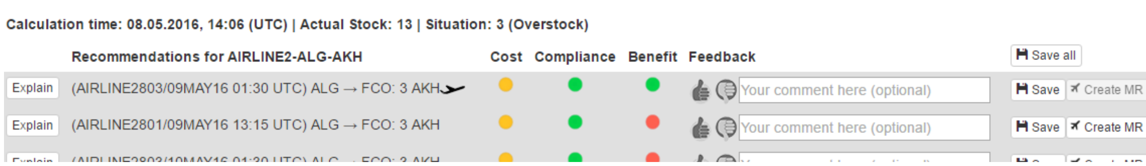

Figure 6. Snapshot of the latest implemented Prototype-3's user interface

Evaluation

We presented the system in two workshops to nearly all ULD controllers and interpreted (1) feedback collected through the system, (2) direct feedback from the participatory observation with ULD controllers, and (3) quantitative measures underlining the usefulness and utility of the evolved artifact. To accumulate evidence for the human-machine symbiosis potential of our instantiated IT artifact, we began to operate the artifact in parallel with daily business and collect data about the system's recommendations and real instructed movements so we could compare and analyze results. Our first finding is illustrated in Figure 7, which presents a comparison of instructed movements for a mid-size European airline and customer of ULD-Provider during a 13-month period (November 2014 – November 2015) with recommendations generated by the system. We came up with coverage of 83 percent with standard deviation of 10 percent on a monthly basis and reasonable variation in: (1) the summer months with the slump, since ULD controllers vary widely in standard procedures to cope with seasonal summer peaks; and (2) November 2015, with the increase of 9 percent over average, up to 92 percent, explained through the extension of the initial knowledge base (by new facts and rules) to, for example, train the system to take hub-spoke structures into account.

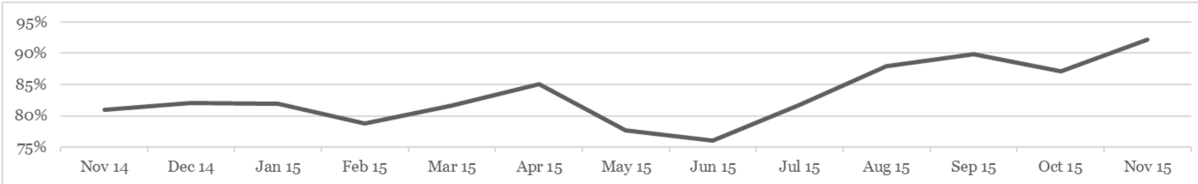

Figure 7. Coverage of real movement decisions also recommended by the system

Our second finding is illustrated in Figure 8. Using the SAW method implemented in Prototype-2, we accumulated the share of situations at the airport that had the potential to select a better alternative (with respect to our given scoring schema) and showed that, on average, every fifth decision provided the potential for improvement. These results give an indication, taking into account our prototypical state of the system, that Licklider's hypothesis regarding performance of human-machine symbiosis holds for the case of ULD resource allocation.

Figure 8. Potential of improvement in given situations

Discussion of Findings

This work makes two main contributions to the literature. First, it sheds new light on the problem class we refer to as the design of IT artifacts for purposeful IS automation and finding the appropriate level of automation given the specific context and requirements of the decision-making problem at hand. Building upon the STS view and the overarching idea of joint optimization that emerged from our analysis and heuristic theorizing as part of this DSR project, we (1) theorize purposeful IS automation and human-machine symbiosis in IS design, (2) extend the related literature in this area, and (3) illustrate a path for achieving an appropriate level of automation in organizational decision making.

The novelty about our proposed concept is that it entails a technologically radical but socio-economically conservative perspective (Simon 1977) and captures the materializing idea that (1) from a technological perspective, full automation of decision-making in organizational context is (party or fully) possible, but that at the same time, (2) from a socio-economic perspective, full automation is either not possible or not desirable because, for example, humans in a largely automated system still desire to participate or because regulations and other constraints require them to do so. As such, the resolution of the conflict challenges the prevalent assumption in the literature that the main factor driving human-machine symbiosis choices is that humans have certain qualities machines lack (and vice versa), for which reason full automation is not feasible in the first place. Rather than viewing the complementary and distinct capabilities of humans and machines as the main drivers of IS design decisions embodying the idea of human-machine symbiosis, we argue that in certain contexts and under certain conditions (to be explored in future research), the prevalent perspective of full automation infeasibility due to the different qualities of humans and machines is still the more relevant one for human-machine symbiosis in IS design. However, our findings also suggest that there are contexts and conditions under which the perspective conveyed with the concept of utilizing symbiotic co-evolution in the relationship between human and machine is more relevant (an exploratory analysis of what these might be, based on our specific design experience, was offered earlier).

Second, we provide design theoretical knowledge to the IS design knowledge base in the form of design principles offering prescriptive guidance and answers to the question of how to create information systems that foster human-machine symbiosis. Our documented IS design knowledge extends the literature on decision support systems and human-machine collaboration and postulates that machines support humans, not vice versa. The prevailing view is that the joint system may compensate for the weaknesses and reinforce the strengths of both humans and machines. In our theory development between iterations 1 and 2, we observed a shift from a human-centered (Kaber and Endsley 2004) and decision-supporting perspective to a more machine-centered view. From the latter perspective, humans are responsible for improving the machines' capabilities and, if still needed, are responsible only for final action execution – which in our case is the resulting ULD movement order. While in the past the data analysis and preparation of decisions was, to a large extent, driven by humans, we can observe a trend to delegate a majority of these tasks to machines, which are becoming increasingly able to perform these tasks and come up with reasonable decisions to be carried out or carry out themselves. Our IS design knowledge accounts for the insight from our research that despite the increasing use of automation, human experts remain an integral part of successful decision making in digitalizing environments. Our study thus extends previous findings about job automation (Chui et al. 2015), suggesting that it is less about automating individual jobs completely and more about automating the activities within occupations and redefining roles and processes.

Our nascent design theory contextualizes the notion of joint optimization from STS theory to the level of IT artifact design, contributing to the respective literature in this area. Abstracting our emergent set of design principles, we theorized three subsets embodying a human-centered perspective, machine-centered perspective, and blending the two from a holistic perspective, which was guided by the idea of joint optimization from STS theory. Synthesizing the learnings from our heuristic theorizing process, we derived the following set of design principles for Human-Machine Symbiosis (see Table 3).

Design Principle Category	Specific Design Principle Statements The artifact should …	Rationales from Heuristic Theorizing
Augmentation (DP-A)	… *align* machine inference with human problem solving. … provide human expert users with *transparency* about the generation of machine inferences. … provide human expert users with *a level of confidence* about suggested action alternatives.	Human-centered perspective: Machines are the assistants of humans to achieve humans' goals of automation, information, or augmentation. Depending on the activities, we observed tasks in which humans' limited cognitive capacities can be enhanced or automated by machine capabilities.
Heteromation (DP-H)	… encourage human expert users to *feed* the machine with new information (facts and rules). … enable the machine to identify and *alert* about missing knowledge autonomously.	Machine-centered perspective: Humans are the assistants of machines to achieve machines' goals to amplify human cognition. Depending on the activities, we observed tasks in which machine routine capabilities can be improved by humans.
Symbiotic Coevolution (DP-S)	… *reduce friction* between human expert users and the machine. … be capable of *continuous extension* of the scope and variety of information processing. … be *adaptable* to the current stage of the evolving human-machine relationship. … enable human expert users to configure the *level of automation* (degree and scope). … provide *holistic performance measurement* of the system as a whole (the combination of human expert users and the machine).	Socio-technical perspective: The artifact is embedded within and reacts to changes in its (1) technological and social-evolutionary environment and (2) human-machine relationship.

Table 3. Derived Design Principles for Human-Machine Symbiosis

Conclusion

In summary, technological advances increasingly allow for automation, but laws, regulations, and other socio-economic constraints hinder companies from fully exploiting automation potentials. In this paper and based on this insight, we theorize the purposeful IS automation in digitalizing environments and integrate corresponding IS design knowledge into the literature. With our findings, we complement and extend previous studies that have focused on the distinct abilities of humans and machines, respectively, as the main factors for explaining design choices related to human-machine symbiosis. Our findings suggest the need to rethink fundamentally the relationship between humans and machines as well as the factors that drive the IS design choices of human-machine symbiosis.

We recognize the need to examine the proposed taxonomy of level of automation to consider specific requirements for human-machines symbioses, and we further developed this taxonomy as we adapted it for our particular case. Furthermore, we identify the need to analyze closely proposed levels of automation in relationship to task characteristics (e.g., complexity, criticality, or urgency) as we assume dependence between them by allowing more automation for rather ordinary repetitive task and more human control for extraordinary singular problems. We identify the need to define what kinds of task characteristics might benefit from human-machine symbiosis to understand and support the possible automation developments.

Our research has certain limitations when it comes to being generalized because our purposed design principles were built and evaluated with one company in one domain. Nevertheless, our DPs can form the basis for further research generalized to contexts other than air transportation logistics in which IS automation must be achieved under similar conditions.

To contribute to a more profound understanding of the observed symbiotic co-evolution, further research should also focus on the factors that trigger changes and scrutinize the mutual influence of these factors.

Appendix

Type of Activity	Description
Design workshop	Since the project began in 2012, the University team and ULD-Provider project team has conducted 1-day design workshops on a monthly basis. Regarding the artifact, the objectives of the design workshops have been to (1) discuss the observed phenomena and findings from data collection and analysis activities, (2) verify the latest problem understanding and solution design, e.g., verify the flow charts (see Iteration-1) and the implementation of the scoring schema (see Prototype-2), and (3) discuss further necessary refinements of the requirements and artifact design. Workshop participants typically include the CIO, employees of the IT department, the COO, employees of the Operations department, and ULD controllers. The CFO and CEO participate if their specific input and feedback are required. Workshop results have been documented in pictures, PowerPoint presentation, and meeting notes, which were approved afterwards.
Observation of ULD controllers	For the initial problem understanding, later refinements, and evaluation purposes of the artifact design, we have conducted participatory observations with five ULD controllers (responsible for four different airlines with individual resource allocation policies) at their desks. In 2013, we observed ULD resource allocation without the artifact in use. In 2014 and 2015, we observed ULD resource allocation with Prototype-2 and Prototype-3. The sessions have been documented via reports, screenshots, and audio records. The documents are analyzed according to themes (e.g., decision-making process, exploitation of data sources) and presented in design workshops for verification.
Focus groups	We have conducted focus groups for evaluation purposes. The objectives of the focus groups have been to confirm the artifact solution and explore further improvements in the design. The sessions are moderated by the university team and participants are encouraged to communicate openly and offer feedback. The results are documented in notes and presented in design workshops. In September 2013, the implemented proof-of-concept Prototype-1 was presented to ULD controllers. The participants were two ULD controllers and two employees of ULD-Provider's IT department.
Interviews	We have also conducted structured interviews for evaluation purposes of Prototype-1 with employees of the IT department. These interviews were guided by the DSS evaluation literature (e.g., Sprague and Carlson 1982). Interviews were documented in notes and presented in design workshops.
Informal feedback	The project team presented the prototype instantiation during *jour fixes* of ULD controllers. Two presentations were held during *jour fixes* of the German ULD controllers (July 2015 and September 2015) and a third presentation was held during a workshop with international ULD controllers (November 2015). The open atmosphere invites valuable, constructive feedback, which is documented in notes and memory logs. The feedback has been structured and discussed in design workshops.
Artifact 's feedback functionality	Since July 2015, we have received feedback via the artifact's feedback functionality (see Figure 5). This feedback has the considerable advantage of reproducing a large part of the decision-making context. Eight ULD controller (responsible for 13 customers) provide continuous feedback. The feedback is analyzed and structured to thematic issues that are discussed in design workshops. In case of uncertainties or ambiguities, we approach the feedback providers. The results are documented in e-mail communication and notes, and discussed in design workshops.
Comparison of movement decisions and recommendations	Since August 2014, we have compared movement orders that are created by ULD controllers and the recommendations created by the prototype systems. We also calculate the movement decisions for which better alternatives exist.

Table 4. Overview of fieldwork

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