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Short Paper

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Abstract

Forecasting support systems (FSSs) support demand planners in important forecasting decisions by offering statistical forecasts. However, planners often rely on their judgment more than on system-based advice which can be detrimental to forecast accuracy. This is caused by a lack of understanding and subsequent lack of trust in the FSS and its advice. To address this problem, we explore the potential of extending the traditional static assistance (e.g., manuals, tooltips) with conversational assistance provided by a conversational assistant that answers planners' questions. Drawing on the theory of effective use, we aim to conduct a framed field experiment to investigate whether conversational (vs. static) assistance better supports planners in learning the FSS, increases their trust, and ultimately helps them make more accurate forecasting decisions. With our findings, we aim to contribute to research on FSS design and the body of knowledge on the theory of effective use.

Keywords: Effective Use, Conversational Agent, Forecasting Support System, Framed Field Experiment

Introduction

Demand forecasting is the process of estimating future customer demand over a certain period. It is crucial for the success of most supply chain-based companies because important internal operational, tactical, and strategic decisions depend on the results of demand forecasts (Fildes et al. 2006). Accurate forecasting results have a significant impact on financial savings, the company's competitiveness, supply chain relationships, and customer satisfaction (Moon et al. 2003). Information systems that prepare forecasts and support the forecasting process are referred to as forecasting support systems (FSSs) (Fildes et al. 2006). As a subgroup of decision support systems (DSSs), these systems support demand planners in their forecasting decisions by offering statistical forecasts, written explanations, or recommendations (Montazemi et al. 1996; Önkal et al. 2009). In general, FSSs are developed to provide accurate forecasts that only require human intervention for exceptional circumstances. For example, for regular time series, the statistical forecasts of FSSs are more accurate than forecasting decisions that are purely based on planners' judgment (Fildes et al. 2006).

However, research has shown that system-generated forecasts are too often replaced by forecasts purely based on planners' judgments, which in most cases decreases the effectiveness of the forecasting decision (Fildes et al. 2009; Goodwin et al. 2013). This might not be surprising since decision-makers in general tend to trust their own beliefs more than advice from others as they understand their internal reasons better than those of others (Yaniv & Kleinberger, 2000). Furthermore, humans tend to trust computer-based advice even less than the advice of other humans (Önkal et al. 2009). The lack of trust in DSS, in general, is often caused by a lack of understanding and learning (Gönül et al. 2006). Parikh et al. (2001) showed that assisting users with explanations when using DSS has a positive effect on users' learning and their final decision. Existing FSSs often only provide static support in form of manuals or tooltips that do not facilitate the learning process. Consequently, demand planners need better support in learning the FSS to increase the effective use of FSSs and ultimately the accuracy of their forecasting decisions. According to learning theory, humans learn better when having meaningful interactions with others (Kim 2006). While access to other humans (e.g. colleagues) often is not readily available, technical advances in the field of artificial intelligence (AI) have allowed the creation of human-like conversational assistants (Diederich et al. 2022). These conversational assistants can replicate human-like interaction and therefore could fulfill this crucial need for meaningful interaction through follow-up questions and explanations, similar to how demand planners would interact with their colleagues. Compared to static support in the form of manuals or tooltips, AI-based conversational assistants offer more flexibility and can provide more intelligent assistance to support planners' learning and effective use of FSSs, which may ultimately increase their trust and help them make more accurate forecasting decisions.

Therefore, in a joint research project with a multinational chemical company, we aim to investigate how to support planners' learning of an FSS. In the chemical industry, many products are commodities, resulting in a particularly high pressure on margins and supply chain efficiency (Blackburn et al. 2015). Demand forecasting in the chemical industry is mainly based on historic demand data and it is very difficult to consider potential future challenges for the supply chain such as demand volatility, economic uncertainty, and climate-induced risks (Acar and Gardner 2012). This makes it even more important to develop reliable FSSs for demand planning in this industry. Our industry partner already developed and implemented an FSS that provides statistical forecasts for demand planners. However, even though it has been found to achieve a higher forecast accuracy than human demand planners, the trust in and understanding of the system remained rather low.

Drawing on the theory of effective use (Burton-Jones and Grange 2013), we primarily seek to investigate how conversational assistance in FSS impacts planners' learning. Further, we aim to examine how their learning actions with the conversational assistant influence their level of effective use and the accuracy of their forecasting decisions. Moreover, since Burton-Jones and Grange (2013) suggest that there is a connection between trust and effective use and Goodwin et al. (2013) showed that planners who better understand their FSS have more trust in the system and make better forecasting decisions, we also aim to investigate how trust is interwined with the constructs of the theory of effective use. This leads us to the following research question:

RQ: *How does conversational assistance support planners' learning of an FSS, increase their trust in and effective use of the system, and ultimately help them make more accurate forecasting decisions?*

In this paper, we present our research design that draws upon the theory of effective use to analyze how conversational assistance in FSSs (e.g., explanations and follow-up questions provided by a conversational assistant) impacts planners' learning and effective use of the FSS. With our findings, we expect to contribute to IS literature by offering novel insights on how conversational assistance can improve planners' learning of an FSS. In addition, we aim to contribute design knowledge for supporting FSS users with conversational assistants. Finally, we aim to show that better learning of FSSs affects planners' trust in the system and that learning and trust, in turn, positively impact the resulting forecasting decisions.

This paper starts by introducing the theoretical foundations of FSSs for demand planning, conversational assistants, and the theory of effective use. This is followed by the presentation of the research model, including the hypotheses. Then, the methodology is described and the artifact that is used for the study is explained. Finally, we share our expected contributions and give an outlook on this research project.

Theoretical Foundations

In the following, we introduce the two research fields of FSSs and conversational assistants. Furthermore, we also provide a short introduction to the theory of effective use.

Forecasting Support Systems for Demand Planning

Accurate demand planning is crucial for operational, tactical, and strategic decisions in companies. To support human demand planners, forecasting support systems (FSSs) – a special class of decision support systems (DSSs) – prepare statistical forecasts to support decision-making processes (Fildes et al. 2006). Armstrong (2001) defined an FSS formally as “a set of procedures (typically computer-based) that supports forecasting. It allows the analyst to easily access, organize and analyze a variety of information. It might also enable the analyst to incorporate judgment and monitor forecast accuracy” (p. 8). Therefore, an FSS usually consists of a database with the time series history, a set of quantitative forecasting techniques, and facilities that allow planners’ judgment. Planners’ judgment should only be necessary to consider special factors, such as promotional campaigns and other qualitative information that is not included in the hard data (Fildes et al. 2006). The two main objectives of using FSSs in the forecasting process are “to improve the user’s ability to realize when judgmental intervention is appropriate and to enable the user to apply accurate judgmental interventions when these are appropriate” (Fildes et al. 2006, p. 354). Lawrence et al. (1986) found that on average a combination of both, statistical forecast and planners’ judgment is better than either of them alone.

Particularly in the chemical industry, demand forecasts usually rely on historical data (Acar and Gardner 2012). Although the FSS leads on average to a higher forecast accuracy based on such data than planners’ judgments without using the FSS, planners often do not rely on the results. The antecedents and effects of judgmental adjustments to statistical forecasts were recently studied in various contexts (De Baets and Harvey 2020; Eroglu and Sanders 2022; Lin 2019). A common problem of FSSs is planners’ lack of trust in the system-generated forecasts and the FSS itself (Goodwin et al. 2013). A lack of trust leads to planners changing the statistical forecasts provided by the FSS more often, which in turn has a detrimental effect on forecast accuracy (Goodwin et al. 2013). Existing studies show that a lack of trust can be mitigated by offering different forms of explanations that positively affect planners’ understanding and learning of the FSS (Goodwin et al. 2013). Explanations in FSSs can address three goals: explain a perceived anomaly, supply additional knowledge, and facilitate learning from the system (Gönül et al. 2006). Consequently, planners require support in the form of contextualized assistance to understand and use FSSs effectively in their decision-making processes.

Conversational Assistants

Users are able to converse with conversational assistants (CAs) (also referred to as conversational agents, chatbots, or virtual assistants) either through written or spoken natural language in a turn-by-turn fashion (Diederich et al. 2022). While the underlying technology of natural language processing has improved greatly over the last decades, conversational assistants are not a new concept. Joseph Weizenbaum (1966) already introduced the idea of enabling users to interact through natural language with technological artifacts in the 1960s by developing ELIZA. However, only recently have conversational assistants been introduced and researched in various application areas, such as customer service (Gnewuch et al. 2017), financial advisory (Morana et al. 2020), health care (Prakash and Das 2020), and data analytics (Ruoff and Gnewuch 2021a).

Organizations are often introducing conversational assistants in their information systems and processes for two reasons. First, due to their ability of natural language interaction they provide users intuitive access to existing information systems (McTear et al. 2016) Second, interacting with conversational assistants can provide the feeling of interacting with a human (Seeger et al. 2018; Verhagen et al. 2014). Especially in the context of decision support, conversational assistants are promising as they are able to “aid, assist and advise people in personal and organizational decision situations” (Power et al. 2019, p. 1). However, while recent studies aim to investigate how conversational assistants influence the effective use of (Ruoff and Gnewuch 2021b) and trust in (Seeger et al. 2017) an information system, it is not well understood how conversational assistance influences these constructs and their interplay.

Theory of Effective Use

Almost a decade ago, Burton-Jones and Grange (2013) proposed the theory of effective use. This theory explains the nature and drivers of effective use, which is defined as "using a system in a way that helps attain the goals for using the system" (Burton-Jones and Grange 2013, p. 4). Effective use is conceptualized as an aggregate construct comprising three hierarchical dimensions: transparent interaction, representational fidelity, and informed action (see Table 1). Thus, the user's overall level of effective use is determined by her/his aggregated levels of the three dimensions. However, each lower-level dimension is necessary but not sufficient for the higher-level dimension. For example, if users cannot transparently access the system's representations, they are unlikely to obtain faithful representations during use and therefore take informed actions. In contrast, when users achieve a high level of effective use, they are more effective and efficient in their overall task performance (Burton-Jones and Grange 2013).

In addition, Burton-Jones and Grange (2013) identify two major drivers of effective use: learning and adaptation. Users can take various learning and adaptation actions to improve their level of effective use. On the one hand, users can adapt a system to improve its representations or the users' access to them (e.g., by personalizing the interface). On the other hand, users can take learning actions (see Table 1) to improve their understanding of the system itself or how to obtain and leverage its representations in order to use a system more effectively. For example, users can attend training sessions or study the system's manual. However, the underlying assumption is that learning actions are primarily driven by the user and the system takes a passive role. More specifically, the system offers ways to learn the system, but it does not actively encourage users to do so. In light of the recent technological advances, we believe that today's systems can take a more active role in learning actions. Therefore, we focus on how conversational assistants can support users in learning the system, fidelity, and leveraging its representations.

Construct		**Definition**	**Measurements**
Learning Actions	Learning the System	"any action a user takes to learn the system (its representations, or its surface or physical structure)" (Burton-Jones and Grange 2013)	Survey data (Trieu et al. 2021), chat and log data
	Learning Fidelity	"any action a user takes to learn the extent to which the output from the system faithfully represents the relevant real-world domain" (Burton-Jones and Grange 2013)	Survey data (Trieu et al. 2021), chat and log data
	Learning to Leverage Representations	"any action a user takes to learn how to leverage the output obtained from the system in his/her work" (Burton-Jones and Grange 2013)	Survey data (Trieu et al. 2021), chat and log data
Effective Use	Transparent Interaction	"the extent to which a user is accessing the system's representations unimpeded by its surface and physical structures" (Burton-Jones and Grange 2013)	Survey data (Trieu et al. 2021)
	Representational Fidelity	"the extent to which a user is obtaining representations from the system that faithfully reflect the domain being represented" (Burton-Jones and Grange 2013)	Survey data (Trieu et al. 2021)
	Informed Action	"the extent to which a user acts upon the faithful representations he or she obtains from the system to improve his or her state" (Burton-Jones and Grange 2013)	Survey data (Trieu et al. 2021)
Trust		Trust refers to a willingness to be vulnerable to another entity (Rousseau et al. 1998)	Survey data (Cyr et al. 2009; Turel et al. 2008)
Effectiveness		"A dimension of performance referring to the extent to which a user has attained the goals of the task for which the system was used." (Burton-Jones and Grange 2013)	Difference between planners' judgment and the gold standard

Table 1. Definitions of Key Constructs and Measurements in this Study

Finally, Burton-Jones and Grange (2013) only briefly touch upon the concept of trust, which is particularly important in the context of FSSs where users need to rely on the system forecasts to make important job decisions. Burton-Jones and Grange (2013) state that "representational fidelity should engender feelings of trust" (p. 653). More specifically, "when representational fidelity increases, users are more likely to trust their systems because they will have more positive expectations of the consequences of relying on those representations" (p. 653). Despite these considerations, the theory of effective use and trust so far have not been integrated and were only studied in isolation. Given that trust plays a crucial role in the context of FSSs, we also address this gap by examining how trust mediates the relationship between representations fidelity and effectiveness.

Research Model

The primary focus of this research is to investigate the relationship between the type of assistance an FSS provides (i.e., conversational vs. static) and the extent to which demand planners engage in learning. Furthermore, we aim to understand how their level of representational fidelity influences their trust and how their trust in turn affects the effectiveness of using the FSS. Our research model which is based on the theory of effective use by Burton-Jones & Grange (2013) is shown in Figure 1. Although the original theory of effective use includes more relationships, we focus only on those relationships that directly relate to our hypothesized effects.

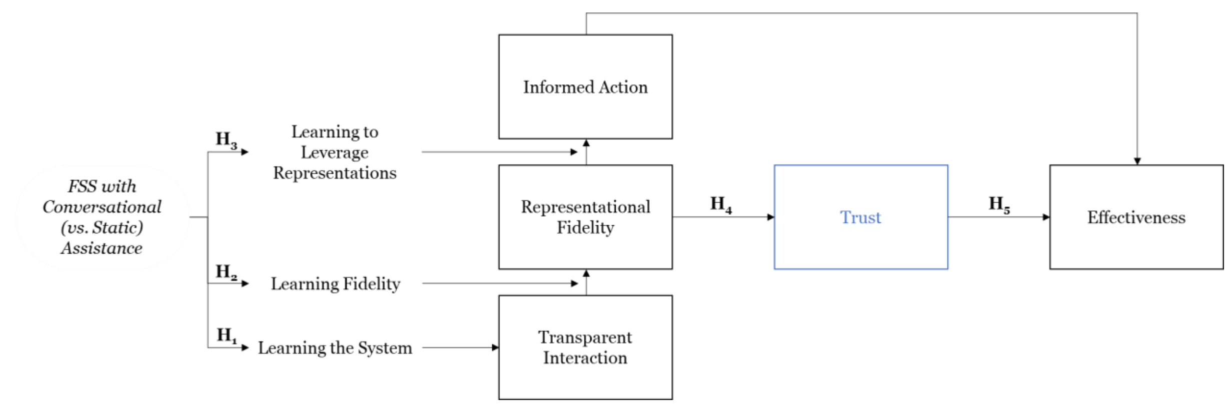

Figure 1. Research Model

The theory of effective use distinguishes three different types of learning actions that users can take to improve their level of effective use: (1) learning the system, (2) learning fidelity, and (3) learning to leverage representations (Burton-Jones and Grange 2013; Trieu et al. 2021). Traditional FSSs enable these learning actions by providing static assistance to users in the form of user manuals and tooltips. Planners can then search for the required information and explanations themselves during the interaction with the FSS. However, according to learning theory, humans can learn better when having meaningful interactions with others (Kim 2006). Conversational assistants can mimic human-like interaction and therefore could fulfill this crucial need for meaningful interaction through follow-up questions and explanations (Diederich et al. 2022). As conversational assistants are more flexible in supporting planners than simple textual support, we argue that the presence of a conversational assistant positively impacts the extent of user learning. Accordingly, we propose our first hypotheses (H_1, H_2, and H_3) as follows:

H_1, H_2, H_3: Planners who interact with an FSS that provides conversational (vs. static) assistance engage more in learning the system (H_1), learning fidelity (H_2), and learning to leverage representations (H_3).

Representational fidelity describes the extent to which planners obtain representations from the system as faithful (Burton-Jones and Grange 2013). As faith and trust are directly connected (McKnight et al. 2011), we propose that representational fidelity has a positive impact on planners' trust in the system. This relationship was also already assumed by Burton-Jones and Grange (2013) who state that "representational fidelity should engender feelings of trust" (p. 653). More specifically, they argue that increasing representational fidelity will lead to users having more positive expectations when relying on the system's representations which in turn affects their trust in the system. Therefore, we formulate our fourth hypothesis:

H_4: A higher level of representational fidelity when using an FSS increases planners' trust in the FSS.

Burton-Jones and Grange (2013) also suggest that trust in the system has a positive impact on the effectiveness of the system usage. When planners trust the system, they are more willing to rely on the forecasts generated by it. Given that these system-generated forecasts are typically more accurate than the planners' judgment, it is likely that planners can then make better forecasting decisions. In our context, we therefore propose that when users trust the system and its representations, they are more likely to consider the information provided in the FSS in their final decision which should lead to a more accurate forecasting decision. This leads to H_5:

H_5: A higher level of planners' trust in the FSS leads to higher effectiveness when using the FSS.

Methodology

Experimental Design. We plan to conduct a framed field experiment to empirically test our research model. To enhance the external validity of the experiment, we developed a custom FSS similar to the one developed and used by our industry partner, a multinational chemical company. Our custom FSS contains the core functionalities of the FSS of our industry partner, but some very specific functionalities and settings were left out to not introduce any confounding factors caused by too complex functionalities and ensure internal validity. We use a between-subjects design with two conditions (conversational vs. static assistance). The control group will be provided with the FSS that only provides static assistance in the form of an integrated manual and tooltips. The treatment group will use the same FSS but with additional conversational assistance provided by a conversational assistant. A screenshot of the FSS with conversational assistance is shown in Figure 2 and its user interface (UI) and functionalities are described below.

Artifact. In both conditions, the FSS contains two main views: an overview table that shows all products (e.g., paint) that are managed by the current user and some additional details like the country, the segmentation, and the seasonality. The second screen provides a deep dive into the forecast of a specific product. On top, a graph is shown that displays the historical actual demand, the forecasted demands, and the future open orders (1). Below, three tabs are included. The first one shows the numbers that belong to the main graph. The second one offers additional information on the product and the forecasts (2). In the third tab, the tested methods are listed and information on forecast accuracy and forecast errors is presented. For assistance on the UI, the FSS includes a manual that can be accessed via the *information* icon in the upper right corner (3). This manual provides information on how to interact with the UI (e.g., how to zoom in on a specific period in the graph) and where to find which information. To understand the representations in the UI (e.g., open orders), explanations for specific terms and information can be accessed via tooltips (4). In addition, the treatment group includes a text-based conversational assistant that can be accessed via the chat icon in the lower right corner (5).

The conversational assistant supports the three learning actions proposed in the theory of effective use as follows. For enabling users to *learn the system,* the conversational assistant can explain to planners where to find a piece of specific information and can explain what the information and terms that are presented in the FSS mean. To address the *learning of representations*, the conversational assistant can explain to planners how they can check if the information and data presented are accurate. Finally, to support planners in *learning to leverage representations*, the conversational assistant can answer questions on processing and using the information of the FSS to fulfill the planning task. When starting the FSS, the conversational assistant proactively offers questions planners could ask. Furthermore, it suggests follow-up questions regarding related terms or questions that address the same term but another type of learning.

Experimental Task. Each participant is randomly assigned to one of the two experimental conditions. After receiving a short introduction to the task and the FSS, participants read additional information on their product like the market trend, historical data, and the prior accuracy of the forecast and the planning decision. Subsequently, they are tasked with forecasting the demand for their product for the next six months.

Participants. We will recruit the participants for our study at our industry partner. These participants are actual employees who work in the supply chain management departments and are thereby familiar with the task, the FSS, and the related information and terms. Participation will be voluntary, and participants will be incentivized by receiving an overview of their forecasting performance compared to other participants. To avoid bias effects, individuals who were involved in the experimental design or participated in initial exploratory interviews are excluded from the study.

Measurement. For the evaluation, we use both survey and log data. The measurements for each construct are listed in Table 1. We adopt established and validated measurement items provided by Trieu et al. (2021) for measuring learning actions, transparent interaction, representational fidelity, and informed action. Additionally, we analyze the log data of UI interactions and chat messages. By analyzing the questions that participants ask the CA and the tooltips they access during the experiment, we can measure how extensively they engaged in each learning action. For measuring trust, we use five items from existing studies (e.g., Cyr et al. (2009), Turel et al. (2008)). By doing so, we can ensure that the trust items fit our context and our system. Effectiveness is defined by the accuracy of the forecasting decision and measured by comparing six planning values that participants must enter to a gold standard based on historical data, which is usually the actual demand for the respective month. In some exceptional cases, e.g., when the statistical forecast considered open orders that increased the statistical forecast to a value that is higher than the actual forecast, the gold standard is represented by the values of the open orders. For being able to compare the planned values with the actual demand, we present to participants data from the previous year. We are controlling for multiple demographic characteristics (age, gender, location) and further characteristics of participants that might impact the results (trusting stance, experience with CAs, experience with the FSS, experience with demand forecasting in general) as well as characteristics of the FSS like the forecasting accuracy for the specific forecast.

Analysis. We will conduct a manipulation check to verify the effectiveness of our treatment assignment by collecting data on whether or not participants in the treatment group interacted with our conversational assistant. Subsequently, we will test our research model using structural equation modeling.

Figure 2. FSS Artifact used in the Experiment (Treatment Group shown) with (1) Graph with Forecast Data, (2) Additional Information on Forecast, (3) Manual and (4) Tooltips for Static Assistance, and (5) Conversational Assistance.

Discussion and Outlook

The effective use of FSSs is of critical importance for many supply chain-based organizations because forecasting decisions have a major impact on business outcomes such as financial savings, the company's competitiveness, supply chain relationships, and customer satisfaction (Moon et al. 2003). However, demand planners often struggle to understand forecasts provided by an FSS, do not trust them, and end up adjusting them mistakenly (Fildes et al. 2009; Goodwin et al. 2013). In our study, we address this challenge by investigating whether and how extending traditional FSSs with a conversational assistant that supports planners in learning the system and its representations and leveraging these representations can help planners to trust the system, use the FSS more effectively, and make more accurate decisions.

Our next step is to conduct our framed field experiment and collect data at our industry partner. We have already developed the custom FSS and the conversational assistant, and the experiment is planned to be conducted in the next months. With our findings, we plan to contribute to research on FSS design and the body of knowledge on the theory of effective use. From a theoretical perspective, we aim to show how combining a traditional FSS with a conversational assistant that supports planners in learning the FSS can increase effective use of FSSs. In addition, we aim to contribute design knowledge for supporting FSS users with conversational assistance. Furthermore, we aim to contribute by offering novel insights on how learning of FSSs affects planners' trust in the system and how learning and trust, in turn, impact the accuracy of the resulting forecasting decisions. The results will help to design better and more effective FSSs. From a practical perspective, the results of our framed field experiment will help our industry partner and other practitioners to understand how to support demand planners in learning the FSS and more specifically how to provide conversational assistance in an FSS. The conversational assistant that we developed will serve as a starting point for our industry partner to develop a fully operational conversational FSS.

Although a framed field experiment has many strengths such as collecting data in a real-world context with actual demand planners, this type of experiment also has its limitations. Our research model will only be tested in a particular scenario and our findings could be influenced by specific characteristics of our industry partner or their FSS which inspired the artifact for our experiment. Furthermore, our study only considers the learning actions described in the theory of effective use, not the adaptation actions. Similarly, we only investigate the effectiveness but not the efficiency of using the FSS as a dependent variable. Therefore, future research could expand upon our study by investigating how planners could be supported in adapting the FSS and how these adaptation actions affect their forecasting decisions. Moreover, it would also be interesting to explore how conversational assistance impacts the efficiency of demand planning.

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