Determinants of feedback effectiveness in production planning

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Abstract

Purpose – The focus is the interplay of cognitive capabilities (mathematical understanding and heuristic problem solving) and learning from feedback. Furthermore, the authors analyze the role of individual factors in designing appropriate feedback systems for complex decision-making situations. Based on a learning model the purpose of this paper is to present an experimental study analyzing the feedback effectiveness in a repeated complex production planning task. Referring to individual characteristics in terms of educational background and problem solving capabilities of the decision maker the authors compare different forms of feedback systems.

Design/methodology/approach – The authors performed four experiments bi-weekly based on a realistic production planning situation. Participants received – depending on the treatment – different types of feedback concerning the final outcomes of the production plans. For testing the hypotheses, the authors conducted ANCOVAs and additional *post hoc* tests for each subgroup to explore the effects of different types of feedback on the subgroups' decision-making performance.

Findings – The authors show that feedback information is not always helpful, but due to acquired knowledge and problem solving capabilities can even be harmful. The authors also show that, depending on the decision maker's individual characteristics and her past performance, the type of feedback is crucial for the learning process.

Practical implications – The study provides important information about feedback design taking individual characteristics of decision makers (educational background, work experience) into account. Applying the results of the study can increase decision-making performance and enhance learning of production planning tasks.

Originality/value – The findings extend previous literature reporting that the performance in complex decision-making tasks depends on educational background and on the ability to cope with the phenomena of cognitive load, working memory limitations and the capability to utilize relevant heuristics to prevent information overload. Some of our results, e.g., the negative impact of non-financial feedback of high-performing economists, contradict the general findings in the literature.

Keywords Management accounting, Knowledge management, Continuous improvement, Decision processes

Paper type Research paper

1. Introduction

The increasing complexity of business processes manifests in more demanding work for decision makers involved in production planning and scheduling tasks (Fransoo and Wiers, 2006; Gasser *et al.*, 2011). Consequently, production planning tasks continuously change and employees in operations management have to learn complex tasks frequently

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(Hopp *et al.*, 2009). This development does not allow them to anticipate all of the consequences of their decisions due to limitations of human cognitive capabilities (Simon, 1956; Tversky and Kahneman, 1974). Typically, such situations require heuristic decision-making approaches to achieve an effective resolution (Kleinmuntz, 1985; Gino and Pisano, 2008). In our experimental study, we address how feedback and performance measurement systems can help decision makers to improve performance in decision-making tasks. In this context, we analyze the role of individual factors in terms of educational background and problem solving capabilities.

The behavioral operations management literature has extensively addressed the role of feedback systems for learning processes and behavioral regulation (Bendoly *et al.*, 2010; Croson *et al.*, 2013). While Sharda *et al.* (1988) explore learning and improvements in decision-making quality, connections between planning tasks, learning and behavioral issues such as cognitive limitations of decision makers have been researched (e.g. Crawford and Wiers, 2001; Bendoly *et al.*, 2006).

Although the literature on decision support systems has analyzed the influence of decision makers' characteristics on the design of task information presentation (e.g. Power and Sharda, 2007), little attention has been paid to the effects of feedback information in this context. Studying the joint effects of educational background and feedback is important because in practice decision makers with different educational backgrounds, problem solving capabilities and knowledge are engaged in complex production planning tasks. Specifically, many firms in the industrial sector employ a mix of employees with technical (engineering) and managerial (economic) backgrounds. Due to their differences it is essential to reveal by which type of feedback systems decision makers can be supported in problem solving. This is in particular relevant with respect to the employment of new employees who have to deal with and learn new decision-making tasks in terms of production planning they are not familiar with.

The purpose of this paper is to bridge the discussed research gap and to address the following research questions:

RQ1. To what extent does the quality of complex decision-making depend on individual factors in terms of educational background?

RQ2. Is the same type of feedback information equally beneficial for high and low performers in complex decision making?

RQ3. What type of feedback information is most beneficial when individual factors and problem solving capabilities are taken into account?

The remainder of this paper is organized as follows. The next section develops the theoretical foundation of our learning model for complex decision making in production planning and derives hypotheses to be tested. In the Section 3 we describe the design of our experimental study. Research outcomes and implications of our findings are discussed in the Sections 4 and 5.

2. Theory development and hypotheses

2.1 Learning complex production planning tasks

Production planning tasks are regarded as complex decision-making problems (e.g. Holt *et al.*, 1960; Davis and Kotterman, 1994). Task complexity either manifests in task difficulty, referring to the cognitive effort that a task requires (Kahneman, 1973; Campbell, 1988), or the task structure, which refers to task specification, i.e., the steps to follow to successfully perform a task (Simon, 1973). A complex task, as opposed to a noncomplex task, is determined by a large number of variables or elements to be considered interdependently or simultaneously (Campbell, 1988; Anderson *et al.*, 1999). Complex tasks imply high information load (Sutcliffe and Weick, 2008) and due to cognitive limitations decision makers are unable to process all information provided (Ford *et al.*, 1989), which is referred to as information overload (Schick *et al.*, 1990).

Production planning tasks require mathematical understanding resulting in problem solving abilities. In practice, decision makers, specifically on the shop floor, usually do not have access to decision support systems or operations research software and must develop and rely on rules of thumb or heuristics to reduce the complexity (Goldstein and Gigerenzer, 2002). The ability to recognize information patterns (Gobet and Simon, 1998; Brewster, 2011) is closely connected to the process of retrieving items stored in the decision maker's memory. As complex production planning tasks are structured in a specific way, the retrieval of previously stored information patterns and their utilization is helpful to reduce information overload (Simon, 1990; Clark *et al.*, 2006).

Previous literature on complex decision making (e.g. Bonner, 2008) has pointed out that in-depth knowledge about the decision problem and the heuristics of how to solve the problems positively affect the decision quality. The quality of the heuristics being developed is determined by the methodological capabilities and the available knowledge of the decision maker she or he can make use of (Brewster, 2011). The creation of knowledge is closely related to organizational learning processes and the implementation of different management techniques (Nold, 2011). They contribute to the development and refinement of heuristics when the decision maker is confronted with a new decision-making problem she or he is not familiar with. Learning can be regarded as "the process of individuals which results in the formation and development of knowledge […]" (Vera and Crossan, 2003). Learning occurs autonomously when a task is repeatedly performed (Lapré *et al.*, 2000), even when no other mechanisms of knowledge transfer are applied (Letmathe *et al.*, 2012). Learning from feedback is often considered to be effective for improving pattern recognition and problem solving capabilities (Bonner, 2008). A repeatedly performed decision-making task becomes part of the decision maker's knowledge and heuristic thinking (e.g. Pennington and Hastie, 1988). The formation of the decision maker's knowledge and cognitive heuristics demands a dynamic learning process over the course of time, consisting of several phases to improve and adjust the heuristics for the purpose of improving decision-making quality. In this context, feedback processes due to a repetition of the decision-making task serve as an important influential factor when individuals are confronted with a new task to learn (e.g. Mory, 2004; Gredler, 2005).

Learning a new task primarily takes place in subsequent learning phases (Bonner, 2008). In the following, we refer to the following types of knowledge related to the learning process of a decision-making task: episodic knowledge, declarative knowledge, and procedural knowledge. The literature has discussed these types of knowledge and it has proved their relevance to develop problem solving capabilities in decision making (e.g. Bonner and Pennington, 1991; Campbell *et al.*, 1996).

Episodic knowledge constitutes the details of personal experience, i.e., important details of facts and concepts. Declarative knowledge is built from interpretations of facts and concepts. Procedural knowledge reflects general decision-making principles that are derived from a repeated utilization of declarative knowledge. It helps to build an in-depth understanding of a complex decision-making problem over the course of time and can be regarded as knowledge of cause-and-effect chains (Bonner, 2008).

While learning a new task, decision makers in the "initialization" phase first acquire episodic knowledge through their own experience when encoding task information for the first time (Dearman and Shields, 2001). In this phase, decision makers are greatly affected by autonomous learning. Autonomous learning automatically occurs during work activities and may be regarded as a consequence of a repetition of work processes or "learning by doing" (Lapré *et al.*, 2000). Although autonomous learning does not require intentional learning efforts, it can foster the development of skills to recognize information patterns and it can help in acquiring the capability to solve problems due to a better mathematical understanding.

During the subsequent "understanding" phase decision makers can use previous experience to retrieve information efficiently, form patterns and build suitable heuristics to amplify learning processes with the help of feedback (Greve, 2003). Although some literature has revealed that with regard to continuous improvement and learning the impact of feedback may depend on the decision-making context (e.g. Sterman, 1989), other research has proved that feedback related to the decision-making performance of individuals is an important factor for learning processes (e.g. Earley *et al.*, 1990; Kluger and DeNisi, 1996). Gasser *et al.* (2011) emphasize that decision makers in production planning should be provided with information in terms of continuous feedback to support learning processes and the formation of relevant knowledge and problem solving capabilities. With the help of feedback, decision makers in the "understanding" phase develop such declarative and procedural knowledge when they repeatedly perform the task several times.

In terms of outcome feedback, learning can take place when decision makers analyze previous outcomes and make the necessary adjustments to their cognitive processes (Djamasbi and Loiacono, 2008). However, outcome feedback information in addition to information on the production planning task increases the information load of decision makers and can result in information overload (Johnson and Payne, 1985; Eppler and Mengis, 2004; Sutcliffe and Weick, 2008). Thus, outcome feedback does not automatically improve learning and decision-making performance, particularly in a complex task, but its effects depend on individual characteristics of the decision maker (Balzer *et al.*, 1989; Kluger and DeNisi, 1996). In this context, the influence of a decision maker's experience with the decision-making task and her or his expertise play an important role because prior experience from education helps to understand task structures and link feedback information with task information (Haerem and Rau, 2007). The educational background therefore serves as a mediator between feedback and the development of declarative and procedural knowledge.

The "continuous improvement" phase finally stimulates suggestions to be made for future process improvements aiming at better decision outcomes. In this phase, additional learning is induced, but this learning is more sophisticated and builds on the procedural knowledge necessary to solve the production planning task from the previous phases. Figure 1 illustrates relevant factors that influence decision-making performance when learning new complex production planning tasks.

With respect to the learning process and decision-making performance, we further expect dependencies between the three learning phases in terms of the effectiveness of feedback information due to individual differences in terms of working memory capacity (Barrett *et al.*, 2004). Taking into account the aspect of an increased information load from feedback, decision makers with a high performance in a preceding phase (indicating a high problem solving capability and task understanding) are predicted to better encode the feedback information in a subsequent phase

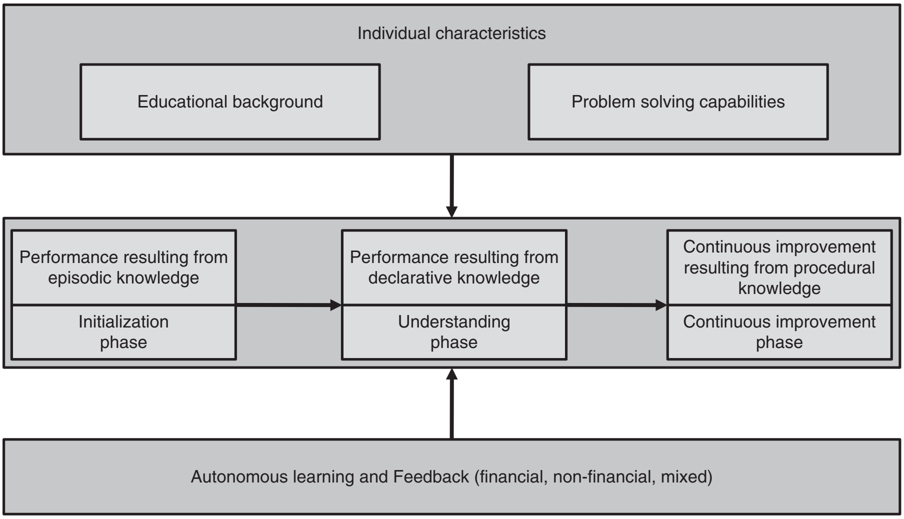

Figure 1.
Research model

compared to low performers. Consequently, they also build a deeper and more refined knowledge which not only directly influences performance, but also mediates the subsequent learning processes (e.g. Choo *et al.*, 2007). A positive correlation between task performance and the problem solving capabilities due to the development of decision-making knowledge can be assumed. Referring to feedback provided, high performers are likely to obtain more benefit from additional feedback due to their ability to process the additional information, helping them to adjust their behavior and heuristics. This is due to the fact that high performers can combine several pieces of information into patterns, allowing them to store more information and to better distinguish between relevant and irrelevant information (Chi *et al.*, 1988). In contrast, less knowledgeable decision makers do not recognize such patterns which limit their ability to adjust their method of processing information (e.g. Camerer and Johnson, 1991). Consequently, low performers are generally less able to process and benefit from additional information, regardless of other individual characteristics.

2.2 Influence of educational background

While research has pointed out that feedback can impact an individual's decision-making behavior (Djamasbi and Loiacono, 2008) the literature has discussed other factors affecting decision-making performance such as gender (e.g. Hyde *et al.*, 1990; Chung and Monroe, 1998), age (Taylor, 1975) and quantitative skills. Previous research has emphasized that decision makers with differing educational backgrounds exhibit differences in learning and performance (e.g. Lucas and Nielsen, 1980) as they have different approaches and capabilities to solve problems (Dearborn and Simon, 1958). Different educational backgrounds manifest in different experiences and preexisting knowledge that is helpful to acquire episodic and declarative knowledge (Gredler, 2005; Bonner, 2008).

The few studies that focus on educational background (e.g. Taylor, 1975; Lucas, 1978; Swink, 1995) do not consider production planning tasks in connection with feedback systems. On the basis of a survey study Lucas (1978) points out that situational and personal factors play an important role when individuals use computer-based information for managerial decisions. In this context, education is relevant to improve information-processing abilities and to recognize patterns as it serves as the basis for learning and knowledge development in complex tasks. Moreover, education in different fields shapes the decision makers' educational backgrounds and provides specific problem solving experience (Swink, 1995). If the new task to learn is similar or has comparable patterns to those tasks already learned through education, then the learning process can be faster and higher performance can be achieved (Bonner, 2008).

Production planning requires analytical and mathematical techniques (Fransoo and Wiers, 2006) as well as an in-depth technical understanding and expertise due to specifications of the input and output factors of production processes (Lockyer and Oakland, 1983; D'Netto and Sohal, 1999). Due to their educational background and their ability to learn relevant information patterns we therefore assume that decision makers that are better educated in technical and mathematical problem solving techniques will perform better than those with a less technical and mathematical background because they have got a higher degree of expertise, i.e., a higher sophistication of decision-making problem representation (Chi *et al.*, 1982; Haerem and Rau, 2007). Referring to the different types of relevant knowledge discussed in the previous section, we expect decision makers with a technical educational background to perform better in the subsequent learning phases. In this context, we refer to performance over the course of time as well as we consider performance separately within the three phases. Thus, we derive the following hypotheses:

H1a. Decision makers with a technical educational background outperform decision makers with a non-technical educational background over the course of time in terms of decision-making quality.

H1b. Decision makers with a technical educational background outperform decision makers with a non-technical educational background in the phases "initialization," "understanding" and "continuous improvement" in terms of decision-making quality.

Considering our argumentation with respect to educational background and expertise we assume that the performance advantages of decision makers with a technical educational background over those with a non-technical educational background will also hold when we distinguish between high and low-performing decision makers. This is due to the fact that the development of knowledge over the course of the different learning phases is strongly influenced by the initial expertise, ability and previous educational knowledge a decision maker has before starting learning a new task (Anderson, 1987; Kanfer and Ackerman, 1989). We therefore state the following hypotheses:

H2a. In the "understanding" phase, decision makers with a technical educational background that have performed high in the "initialization" phase outperform decision makers with a non-technical educational background that have performed high in the "initialization" phase in terms of decision-making quality.

H2b. In the "understanding" phase, decision makers with a technical educational background that have performed low in the "initialization" phase outperform decision makers with a non-technical educational background that have performed low in the "initialization" phase in terms of decision-making quality.

H2c. In the "continuous improvement" phase, decision makers with a technical educational background that have performed high in the "understanding" phase outperform decision makers with a non-technical educational background that have performed high in the "understanding" phase in terms of decision-making quality.

H2d. In the "continuous improvement" phase, decision makers with a technical educational background that have performed low in the "understanding" phase outperform decision makers with a non-technical educational background that have performed low in the "understanding" phase in terms of decision-making quality.

2.3 Influence of feedback mechanisms and problem solving capabilities

Bendoly *et al.* (2010) emphasize that it is essential to cautiously and deliberately select the most suitable types of feedback to achieve the highest possible performance. The mostly used feedback in practice is outcome feedback because it has the quality to be understood easily by the decision makers (Goodwin *et al.*, 2004). Reflecting on practice, we refer to three types of outcome feedback: financial feedback in terms of cost information, non-financial feedback in terms of key production performance indicators and efficiency costing as a combination of financial and non-financial feedback.

The first type of feedback, cost information, usually provides decision makers with information about the cost-level achieved for a given production planning period and compares actual costs against expectations (Briers *et al.*, 1999). When actual costs deviate from expected costs, decision makers realize the need of corrective responses and adjust their behavior accordingly. As this type of feedback only provides an indication of existence rather than the cause of potential problems, modifying decision behavior and heuristics is rather difficult and often results in a trial-and-error process, especially in a complex decision-making task (Balzer *et al.*, 1989).

Since financial feedback does not necessarily help to directly understand the underlying causes for performance deviations (Neely *et al.*, 2005) the literature has emphasized the positive effects of non-financial feedback information for continuous improvement and learning (e.g. Ittner and Larcker, 1998). This type of feedback provides information about resource consumption patterns, capacity utilization or scrap rate and is usually provided in terms of key performance indicators. When comparing actual performance against expected performance (costs), non-financial feedback helps to identify the sources of distortions and deviations (Briers *et al.*, 1999). With the help of non-financial performance measures, decision makers are expected to better adjust their cognitive processes and have a higher learning rate compared to when only financial feedback is provided.

Efficiency costing (Letmathe, 2002) provides information about interdependencies and tradeoffs between performance areas such as production processes and is based on the assumption that controllable production costs are given through the difference between actual and ideal costs of production processes. Ideal costs are the lowest possible costs, based upon the costs of ideal production, where no inefficiencies occur. Nicholas (1998) and Liker (2004) define the standards of ideal production through attribute such as no waste of material, no scrap or rework and no waste of processing time. Although ideal standards cannot generally be accomplished, they define a state showing potential directions for improvements. The cost-efficiency level can be determined as the amount of the ideal costs of a cost subject divided by the actual costs of the cost subject. As it is possible to document an overall cost inefficiency level as well as inefficiency levels for different performance (waste) areas quantitatively and monetarily, efficiency costing provides a mixed feedback consisting of non-financial and financial information.

From our earlier discussion we assume that high performers are able to process a higher information load. We therefore expect high performers to benefit from detailed feedback information indicating interdependencies between different entities of a complex production planning task. Additionally, we expect differences to occur depending on individual factors such as educational background, since individual differences influence information processing and pattern recognition both relevant for refining declarative as well as procedural knowledge (Motowidlo *et al.*, 1997). Considering high performers, we in particular expect decision makers with a technical educational background to benefit from other types of feedback than economists. This is due to fact that the presentation structure of the feedback should match the decision maker's cognitive model or internal information representation (Chandra and Krovi, 1999). These insights resulting from the theory of representational congruence (e.g. Arnold *et al.*, 2004) reveal that the representational congruence is relevant to prevent cognitive overload and a negative effect on learning and decision-making performance. High-performing engineers that are used to deal with non-financial, but technical information are therefore expected to benefit more from non-financial or mixed types of feedback. On the other hand, we expect high-performing decision makers with a non-technical educational background to benefit stronger from financial feedback. Contrary to the high performers, we do not expect great effects of different types of feedback in combination with educational background differences, when we refer to low-performing decision makers. These decision makers have to deal with an information overload and any type of feedback will increase cognitive load so we do not expect them to benefit from any type of feedback information at all.

From the preceding analysis we derive the following hypotheses:

H3a. High performers in the "initialization" phase benefit from additional feedback information in the subsequent "understanding" phase. The performance-level depends upon the individual factor educational background as well as the type of feedback.

H3b. Low performers in the "initialization" phase do not benefit from additional feedback information in the "understanding" phase, regardless of individual factors.

H3c. High performers in the "understanding" phase benefit from additional feedback information in the subsequent "continuous improvement" phase. The performance-level depends upon the individual factor educational background as well as the type of feedback.

H3d. Low performers in the "understanding" phase do not benefit from additional feedback information in the "continuous improvement" phase, regardless of individual factors.

3. Experimental design

To test the hypotheses, we performed a controlled experimental study at a major German university with 410 students from the undergraduate course "Introduction to Management Accounting" who had not gained any specific knowledge on operations research methods. We utilize the experimental method, because experiments allow to guarantee internal validity and are considered to be best suitable to investigate cause-and-effect relationships between research constructs (e.g. Aronson *et al.*, 1990). By testing our hypotheses with a highly realistic task, we are able to answer the research questions rigorously and can draw relevant conclusions for decision making in firms.

The average age of the students participating in the experiment was 21.9 years. The students either had a technical educational background (i.e. they were studying an engineering subject) or a non-technical educational background (i.e. they were studying business administration, business law or economics). For simplification, in the following we refer to those participants with a technical educational background as "engineers" and those with a non-technical background as "economists." We performed four experiments bi-weekly. Compared to a one-shot-experiment the time between the experimental sessions allowed subjects to store learned procedures which is an integral part of learning and knowledge development (Gredler, 2005). Additionally, we simulated a realistic production planning situation, i.e., feedback concerning the final outcomes of the production plans is only available after a certain amount of time, when the production processes have been carried out. With reference to our model, the first experiment corresponded to the "initialization" phase, while experiments 2-4 corresponded to the "understanding" phase. The "understanding" phase comprised three experimental sessions, because repeated feedback is essential for declarative and procedural knowledge acquisition and learning, as discussed above.

All participants were introduced to the production planning task, the objectives and the restrictions to consider, as well as the assignment of penalties. The introduction was repeated in every session. Penalties were relevant for product shortages when planned production was lower than demand and for exceeding machine or labor capacity constraints. The penalty per unit was approximately 20 percent higher than the marginal costs in the optimal solution, so that a voluntary under-production or over-utilization of machine and labor capacity was not economically beneficial. After the introduction had been given in the introductory session, participants were divided into four groups through random selection. As the control group, group 1 received no feedback. Group 2 received financial feedback in terms of cost information. Group 3 received feedback in terms of non-financial key production figures. Group 4 was given a feedback report containing cost-efficiency measures. In addition to session-specific documents, at the beginning of the second, third and fourth sessions, every participant received individual feedback reports of all their previous sessions (feedback history).

In each of the four experimental sessions the participants had to solve a complex production planning problem with 21 production processes and three products. In particular, the students had to decide on the optimal choice of production activities to yield a given product output while considering capacity and resource restrictions as well as scrap rates and emissions. The students received full information about all parameters and cost factors. The production activities as well as the available restrictions and conditions were not altered in the different sessions; however, to rule out sole memory effects of the test persons, the level of output of the three products changed in every session, with substantial changes in the product program[1]. The complexity of each task was kept constant by ensuring approximately equal distances to the edge of the solution space. The cost minimum for each problem was 22,400 cost units within the range of ± 1.2 percent. The time to solve the production problem was limited to 30 minutes in each session, and students were allowed to use a calculator. At the end of the fourth experimental session, all participants had to fill in a questionnaire to make continuous improvement suggestions (reflecting the "continuous improvement" phase) with reference to the data situation from the fourth experimental session. Participants were asked to give a maximum of three suggestions indicating which production coefficients, emission coefficients or scrap rates should be halved to potentially reduce production costs. Suggestions were not allowed to include price reductions, relaxation of capacity restrictions or changes in output demand.

For a feasible solution in a session the students received one point for the course's final examination. In each session they could gain an additional point if their solution was better than the best 50 percent within their group[2]. Altogether a maximum of eight points could be obtained (in addition to the 60 points in the final exam). Prior to the start of the first experiment, the students had to fill in a basic questionnaire asking for their gender, subject of study and year of study. The participants' age and risk aversion which we evaluated as controls did not significantly impact the results[3].

4. Results and discussion

Out of the 410 undergraduate students participating in the experiment, we excluded students with missing values (17), other than economic and engineering disciplines (19) and lack of task understanding (82)[4]. These were students who did not calculate a solution or signed in costs instead of production volumes. Additionally, we introduced a cap of maximal cost, i.e., we limited the costs assigned to those students who produced costs that were higher than if no production volume was declared to the (penalty) costs that would be realized in the case of no production of the minimum required production volumes. Following this mechanism, we had 292 datasets for statistical analysis comprising 191 participants from an economic discipline and 101 participants from an engineering discipline.

4.1 Descriptive statistics

For the statistical analysis, decision-making performance for each of the experiments 1-4 was calculated in terms of cost deviations between the costs of the actual decisions of the participants and the optimal costs of the underlying operational research model. High cost deviations indicated low performance, while low cost deviations revealed high performance. The performance of the continuous improvement suggestions was calculated as the difference between the costs in the fourth experiment resulting from the participants' solution and the hypothetical costs of that solution if the continuous improvements proposals were realized. Here, high differences (improvements) indicated a high performance, while low differences (improvements) implied low performance.

Our first hypotheses investigate the influences of individual factors on learning the production planning task. Figure 2 reveals differences between economists and engineers. Typical learning curve effects occurred which are confirmed by the relative improvement over the course of time (Table I). While the economists had a marginally stronger relative improvement in absolute terms over the course of time than the engineers, but the relative the gap between engineers and economists increased from the first (22.67 percent) to the fourth experiment (25.89 percent) by 3.22 percent.

We utilized median splits to differentiate between high and low performers in each subgroup (engineers and economists) with respect to the "initialization" phase. Comparing the performance of the engineers and the economists in the "understanding" phase that performed highly in the preceding "initialization" phase we find that the engineers had a lower deviation from the optimal costs than the economists, i.e., the difference between engineers and economists was

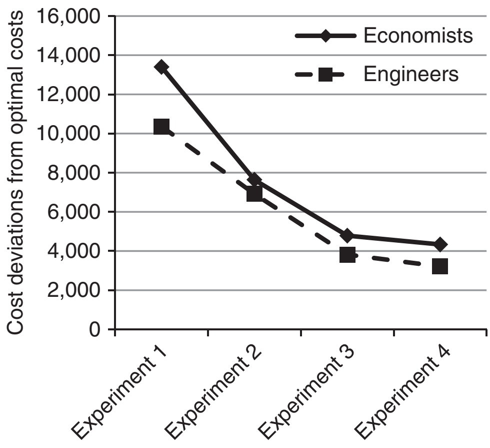

Figure 2. Cost deviations from optimal costs with respect to educational background

Table I. Relative improvement over the course of time

	n	Experiment 1	Experiment 4	Improvement (%)
Economists	191	13,402.53[a]	4,334.99[a]	67.66
Engineers	101	10,358.46[a]	3,212.64[a]	68.99
Difference (absolute)		3,044.07	1,122.35	
Difference (relative)		22.67%	25.89%	

Note: [a]In terms of mean cost deviations from minimum costs

27.46 percent (Figure 3). A comparable, but less distinct difference (11.03 percent) is found for the low-performing engineers and economists.

Utilizing median splits to distinguish between both high and low-performing engineers and economists of the "understanding" phase, we find differences between engineers and economists in terms of the amount of cost savings in the "continuous improvement" phase. Figure 4 reveals for the high performers that the engineers outperformed the economists by 36.65 percent in terms of mean cost savings, while the difference amounts to 25.99 percent for the low performers.

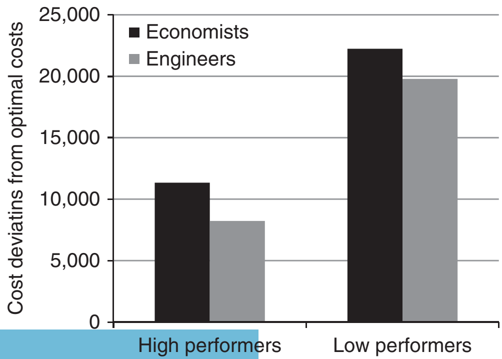

Figure 3. Performance in the "understanding phase" of high and low performers in the "initialization" phase

Figure 5 shows the influences of the different types of feedback in the three learning phases. Cost deviations for the three experimental Sessions 2-4 were cumulated for the "understanding" phase.

In the first experiment, all groups had approximately the same performance level and no significant differences were found. This shows that the affiliation to a particular group did not have any influence on the results, so that we are able to rule out motivational biases resulting from group affiliation. In the "understanding" phase, group 3 receiving non-financial feedback fell behind group 1 that did not receive any feedback. Interestingly, group 2 performed better than groups 3 and 4. In the "continuous improvement" phase the performance levels did not differ much between the four groups.

4.2 Hypotheses testing

For an in-depth analysis, we refer to the results of analyses of covariance (ANCOVAs) with gender as covariate to control for influences of this variable and rule out interferential effects and noise[5]. The descriptive statistical results showing differences over the four experimental sessions (experiments 1-4) between economists and engineers are confirmed by Repeated Measures ANCOVAs (Table II).

Regardless of educational background, the participants significantly ($p = 0.000$) improved over the course of time and therefore we can confirm typically learning

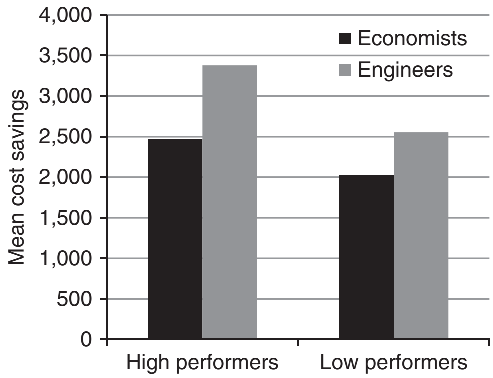

Figure 4.
Performance in the "continuous improvement" phase of high and low performers in the "understanding" phase

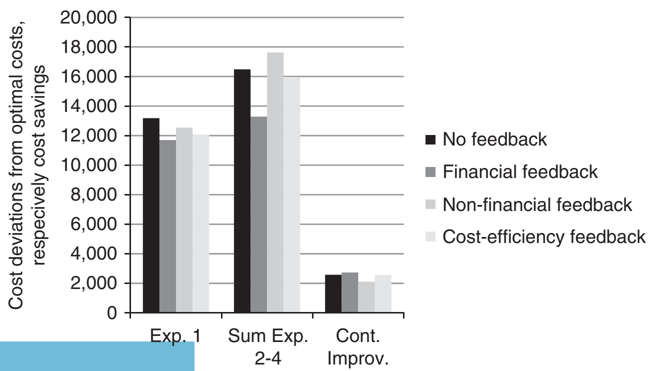

Figure 5.
Comparison of feedback effects

curve effects. As shown before, the descriptive analysis reveals that the engineers outperformed the economists in all phases of the experiment. Although the differences over the course of time are even reinforced from 22.67 to 25.89 percent (Table I), the between-subject-effect does not hold on a significant level ($p = 0.332$) and *H1a* is not supported.

To test *H1b*, we performed ANCOVAs for the three phases of our experiment and compared educational background effects (Table III). We find significant differences between economists and engineers in the "continuous improvement" phase. First, this finding implies that economists and engineers do not differ in the development of episodic and declarative knowledge. Second, it reveals a general advantage of decision makers with a technical educational background over those decision makers with a non-technical educational background with respect to the formation of procedural knowledge. It reflects that over the course of time technical-oriented decision makers develop a more in-depth understanding and a more sophisticated problem understanding due to cognitive and problem solving capabilities than decision makers with an economic background.

The descriptive analyses (Figures 3 and 4) reveal performance differences between engineers and economists in the "understanding" and "continuous improvement" phases. To verify this finding, we performed further ANCOVAs, whereas Table IV contains the result for the differences in the "understanding" phase, while Table V refers to the outcomes of the "continuous improvement" phase. The results of the descriptive analyses are supported for the high-performing decision makers by the results of the ANCOVAs ($p = 0.081$ and $p = 0.070$, respectively), but not for low performers ($p = 0.850$ and $p = 0.541$, respectively). Nevertheless and in line with the

Table II. Educational background differences over the course of time

		Mauchly-test df	Mauchly-test χ^2 approx.	Mauchly-test p	Greenhouse-Geisser-test df	Greenhouse-Geisser-test F	Greenhouse-Geisser-test p
Educational background ($n = 292$)	Factor	5	192.230	0.000	2.136	8.941	0.000***
	Between-subject-effect				1	0.944	0.332

Note: ***Significant on a two-tailed level of $\alpha = 0.010$

Table III. Educational background differences in the three learning phases

Factor	n	Initialization phase df	Initialization phase F	Initialization phase p	Understanding phase df	Understanding phase F	Understanding phase p	Continuous improvement df	Continuous improvement F	Continuous improvement P
Educational background	292	1	1.840	0.176	1	0.215	0.643	1	2.917	0.089*

Note: *Significant on a two-tailed level of $\alpha = 0.100$

Table IV. Educational background differences in the "understanding" phase

Factor	n	Understanding phase df	Understanding phase F	Understanding phase p
High performers in the "initialization" phase	147	1	3.079	0.081*
Low performers in the "initialization" phase	145	1	0.036	0.850

Note: *Significant on a two-tailed level of $\alpha = 0.100$

descriptive results, the hypothesis test shows that the performance of the economists deviates stronger from the performance of the engineers in terms of high performance than in terms of low performance. Therefore, *H2a* and *H2c* are supported by the ANCOVAs on a low significant level, but there is no support from an inductive statistical side for *H2b* and *H2d*.

So far we conclude that engineers with above average expertise are more successful in learning and knowledge development due to a more sophisticated problem understanding in the recognition of patterns and structures of complex production planning tasks. These findings are stronger when we distinguish between high-performing decision makers on the one hand and low-performing decision makers on the other hand which reflects the importance to take problem solving capabilities into consideration.

H3a and *H3b* propose that high performers and low performers process feedback information differently in the "understanding" phase because of differences in information-processing capacity in the "initialization" phase. As we relate our hypotheses to individual characteristics of the decision makers, we designated subgroups of high performers and low performers based upon median splits in the "initialization" phase for economists and engineers[6]. For testing these hypotheses, we conducted an ANCOVA and additional *post hoc* tests for each subgroup to explore the effects of different types of feedback on the subgroups' decision-making performance in the subsequent "understanding" phase.

Table VI shows that in terms of educational background we find significant differences related to the different types of feedback for the best performing economists

Table V. Educational background differences in the "continuous improvement" phase

Factor	n	Continuous improvement phase df	F	p
High performers in the "understanding" phase	146	1	3.341	0.070*
Low performers in the "understanding" phase	146	1	0.376	0.541

Note: *Significant on a two-tailed level of $\alpha = 0.100$

Table VI. Feedback influence in the "understanding" phase of high performers in the "initialization" phase

Subgroup	n	Differences in the understanding phase df	F	p	*Post hoc* (Fisher's LSD) Feedback groups	p	Comparison
Economists	96	3	6.983	0.000***	1 = 2	0.643	
					1 = 3	0.000***	1 > 3
					1 = 4	0.442	
					2 = 3	0.000***	2 > 3
					2 = 4	0.752	
					3 = 4	0.001***	4 > 3
Engineers	51	3	4.056	0.012**	1 = 2	0.006***	2 > 1
					1 = 3	0.002***	3 > 1
					1 = 4	0.031**	4 > 1
					2 = 3	0.609	
					2 = 4	0.635	
					3 = 4	0.349	

Notes: 1, no feedback; 2, financial feedback; 3, non-financial feedback; 4, cost-efficiency feedback. **,***Significant on a two-tailed level of $\alpha = 0.050$; $\alpha = 0.010$, respectively

($p = 0.000$) and engineers ($p = 0.012$). For the economists, we find neither differences between groups 1 and 2 nor between groups 1 and 4. Furthermore, group 1 performs better than group 3. Thus, those economists that did not receive additional feedback information performed no worse than those who received additional feedback. But when we compare the different types of feedback, the *post hoc* tests combined with descriptive statistical results (Table AI) show that non-financial information in terms of key production performance indicators is not an appropriate form of feedback and with regard to this specific task, is even harmful feedback for economists in this learning phase. Results are highly significant for comparison with financial feedback ($p = 0.000$) and non-feedback ($p = 0.000$) respectively. By strong contrast, the best performing engineers benefited from all types of feedback. Financial ($p = 0.006$), non-financial feedback ($p = 0.002$), and efficiency costing feedback ($p = 0.031$) induced higher performance compared to the non-feedback group. Interestingly, we do not find any significant difference among the different types of feedback in this subgroup; only the descriptive analysis suggests an advantage of non-financial feedback. We can summarize that the best performing engineers in the "initialization" phase basically benefited from feedback, but there is no statistically significant feedback preference. Altogether we conclude that *H3a* is partly supported.

Testing *H3b* we find that low-performing economists ($p = 0.371$) and engineers ($p = 0.766$) in the "initialization" phase did not benefit from additional feedback (Table VII). Referring to our argumentation, we can conclude that low performers do not benefit from additional feedback information, as it increases their information load, which low performers, at this stage of their learning curves are not able to utilize for performance improvement. *H3b* is supported.

To test the *H3c* and *H3d*, we followed the same methodology as before, utilizing median splits to differentiate between high and low performers in each subgroup with respect to the "understanding" phase[7]. Afterwards we conducted an ANCOVA and additional *post hoc* tests for each subgroup to explore the effects of different types of feedback on the subgroups' decision-making performance in the subsequent "continuous improvement" phase.

Table VIII shows that the best performing economists in the "understanding" phase did not benefit from feedback information in the "continuous improvement" phase. Differences among the four feedback conditions ($p = 0.881$) proved to be insignificant. On the other hand, we find significant differences in the "continuous improvement" phase for the best performing engineers ($p = 0.048$) of the "understanding" phase. For this subgroup, we find clear evidence of the superiority of the cost-efficiency feedback information. The *post hoc* tests reveal that engineers who were provided with financial ($p = 0.046$) or non-financial feedback ($p = 0.012$) information performed worse in the "continuous improvement" phase than those who received cost-efficiency feedback. Although the results do not support *H3c* for economists, for the engineers as the best performing subgroup in the

			Understanding phase	
Subgroup	n	df	F	p
Economists	95	3	1.058	0.371
Engineers	50	3	0.382	0.766

Note: Feedback influence in the "understanding" phase of low performers in the "initialization" phase

Table VII. Feedback influence of low performers in the "initialization" phase experimental study, mixed financial and non-financial feedback considering interdependencies between different properties of a production planning task and indicating areas of improvement is most beneficial for continuous improvement and learning. This provides evidence that decision makers with a technical educational background that have already reached a high level of performance and possess sufficient declarative and procedural knowledge of a complex decision problem should be provided with sophisticated feedback information to promote further in-depth understanding of the underlying structures of the task.

As stated in *H3d*, low performers in the "understanding" phase did not benefit from additional feedback information in the subsequent "continuous improvement" phase (Table IX). Considering economists, we did not find a significant difference between the different feedback groups ($p = 0.159$). Referring to engineers, we had significant differences among the different types of feedback. However, as expected, low performers in these subgroups basically did not benefit from feedback because the decision makers who did not receive additional feedback outperformed those participants receiving feedback information. Low-performing engineers performed lower when non-financial ($p = 0.035$) or cost-efficiency information ($p = 0.036$) was provided compared to the group without feedback. We draw the conclusion that additional feedback is even harmful for these decision makers because information

Table VIII.
Feedback influence in the "continuous improvement" phase of high performers in the "understanding" phase

		Differences in the continuous improvement phase			*Post hoc* (Fisher's LSD)		
Subgroup	n	df	F	p	Feedback groups	p	Comparison
Economists	96	3	0.221	0.881			
Engineers	50	3	2.854	0.048**	1 = 2	0.435	
					1 = 3	0.732	
					1 = 4	0.020**	4 > 1
					2 = 3	0.563	
					2 = 4	0.046**	4 > 2
					3 = 4	0.012**	4 > 3

Notes: 1, no feedback; 2, financial feedback; 3, non-financial feedback; 4, cost-efficiency feedback. **Significant on a two-tailed level of $\alpha = 0.050$

Table IX.
Feedback influence in the "continuous improvement" phase of low performers in the "understanding" phase

		Differences in the continuous improvement phase			*Post hoc* (Fisher's LSD)		
Subgroup	n	df	F	p	Feedback groups	p	Comparison
Economists	95	3	1.769	0.159			
Engineers	51	3	2.327	0.087*	1 = 2	0.156	
					1 = 3	0.035**	1 > 3
					1 = 4	0.036**	1 > 4
					2 = 3	0.275	
					2 = 4	0.356	
					3 = 4	0.799	

Notes: 1, no feedback; 2, financial feedback; 3, non-financial feedback; 4, cost-efficiency feedback. *,**Significant on a two-tailed level of $\alpha = 0.100$; $\alpha = 0.050$, respectively load rises and impedes the development of procedural knowledge. Whereas cost-efficiency costing outperformed all other feedback systems in terms of continuous improvement for high-performing engineers, it was inferior to other feedback systems for all low performers in the "understanding" phase. Table AIV shows that low-performing economists achieved the greatest continuous improvement when they did not receive any feedback. Similarly, low-performing engineers achieved the greatest continuous improvement of their performance when no feedback was provided. As we were not able to find any evidence that feedback is superior to non-feedback, *H3d* is supported.

Taking into account our results and our learning model, the benefit of feedback information to build declarative and procedural knowledge in the "understanding" and "continuous improvement" phases depends on various factors. By not differentiating between high and low-performing decision makers (Table III), we do not find highly significant differences in the three learning phases with respect to educational background. However, educational background becomes relevant when we take feedback effects into consideration and compare high performers with low performers. Feedback information appears to be most beneficial for those decision makers who have already reached a high performance level and have the capability to encode further feedback information in addition to the task information. They appear to be able to develop an in-depth understanding over the course of time when learning a new task and to orientate their cognitive processes and behavior toward continuous improvement.

5. Conclusions

Our study provides important information about feedback design taking individual characteristics of decision makers (educational background, work experience) into account. Applying the results of our study can increase decision-making performance and enhance learning of production planning tasks. We have shown that the quality of knowledge being acquired is strongly determined by information-processing capabilities and the educational background of the decision maker. Referring to our first research question we found that engineers basically outperform economists. For a new complex production planning task we could show that due to cognitive capacity limitations and information overload feedback information does not automatically result in improved performance. Addressing the second research question we have revealed that high performers with high problem solving capabilities and low performers with lower capabilities process feedback information differently and the impact of feedback information on decision-making quality differs significantly. These results do not only apply to feedback systems in general but there are significant differences among different types of feedback information. Some of the results even show that feedback that is highly beneficial to high performers can be harmful to low performers. We found that non-financial feedback was beneficial to engineers but harmful to economists even within the group of high performers. These findings extend previous literature (e.g. Brewster, 2011) reporting that the performance in complex decision-making tasks depends on the ability to cope with the phenomena of cognitive load, working memory limitations and the capability to utilize relevant heuristics to prevent information overload.

Referring to our third research question we have demonstrated that the advantage of a feedback system is determined by information-processing capabilities and the available expertise due to the educational background of the decision maker. With regard to the relevance of combinations of financial and non-financial feedback our findings are in line with different case studies (Lind, 2001; Van Veen-Dirks, 2006). However, our study furthermore reveals that the management in firms should be aware that employee characteristics have to be taken into consideration when implementing feedback systems to best support learning processes. This means, such decision support systems should meet individual user demands and offer possibilities to individually design feedback systems.

In this context, we emphasize that our results only show statistical differences which cannot be used as a justification for selecting certain decision makers or exercising discriminative behavior. All in all, to control learning processes in the context of production planning, management has to carefully evaluate the impact of a feedback system. Depending on user characteristics, in particular with respect to educational background, the choice for or against a certain type of feedback is important to best support the learning process of decision makers. If user characteristics are disregarded, additional feedback information will not automatically result in increased performance and might even be detrimental to decision-making performance.

Some limitations of our study exist that could be addressed in the future. First, some differences we found in our analyses need more support, especially with respect to a more refined research on the degree of expertise in the context of operations management tasks. Second, as literature has provided mixed results with regard to the influence of social background and personality on the effectiveness of feedback systems in decision making (Bonner, 2008; Strohhecker and Größler, 2013), such topics need further consideration in future studies.

Notes

1. The product programs (Product A, B, C) for the four sessions were: Session 1: 100, 50, 100; Session 2: 110, 40, 90; Session 3: 90, 65, 90; Session 4: 78, 80, 80.
2. Tournaments with a 50 percent share of winners have been proven to create the highest motivation of participants (Harbring and Irlenbusch, 2008).
3. Concerning risk aversion, we derived utility functions for each participant according to the method by McCord and de Neufville (1986). Statistical analyses (ANOVAs) show that risk aversion across the four groups do not differ (0.856, $p=0.465$), even when we just refer to economists (0.682, $p=0.564$), or engineers (0.637, $p=0.593$). Concerning age, we also do not find differences across the groups (0.298, $p=0.827$), also not with respect to economists (0.241, $p=0.867$), or engineers (0.715, $p=0.545$).
4. The relatively high number of participants that did not understand the task is due to the high complexity of the task. This result proves that we chose a sufficiently high complex task as intended.
5. Consistent with findings in the literature (see references in Section 2.2), ANOVAs showed significant performance differences between females and males over the course of time of the four experimental sessions ($F=7.348$, $p=0.007$) and in all three learning phases ("initialization" phase: $F=4.951$, $p=0.027$, "understanding" phase: $F=5.079$, $p=0.025$, "continuous improvement" phase: $F=5.166$, $p=0.024$).
6. The relevant descriptive results for the *H3a-H3b* are documented in the Tables AI and AII.
7. The relevant descriptive results for the *H3c-H3d* are documented in the Tables AIII and AIV.

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Appendix

Subgroup	Feedback group (1)	Feedback group (2)	Feedback group (3)	Feedback group (4)
Economists	6,942.97	8,441.71	18,227.82	9,310.91
Engineers	16,031.37	6,528.25	4,653.53	8,330.50

Note: Mean deviations from optimal solution in the "understanding phase" of high performers in the "initialization" phase

Table AI. Mean cost deviations of high performers in the "initialization" phase

Subgroup	Feedback group (1)	Feedback group (2)	Feedback group (3)	Feedback group (4)
Economists	18,481.69	18,215.72	25,289.59	27,978.12
Engineers	25,218.70	19,429.37	16,913.85	15,347.64

Note: Mean deviations from optimal solution in the "understanding" phase of low performers in the "initialization" phase

Table AII. Mean cost deviations of low performers in the "initialization" phase

Subgroup	Feedback group (1)	Feedback group (2)	Feedback group (3)	Feedback group (4)
Economists	2,262.21	2,663.07	2,408.22	2,550.98
Engineers	2,135.69	3,202.26	2,548.78	5,693.91

Note: Mean cost savings in the "continuous improvement" phase of high performers in the "understanding" phase

Table AIII. Mean cost savings in the "continuous improvement" phase of high performers

Subgroup	Feedback group (1)	Feedback group (2)	Feedback group (3)	Feedback group (4)
Economists	2,297.12	2,685.23	1,799.73	1,617.26
Engineers	3,580.97	2,506.27	1,432.84	1,669.49

Note: Mean cost savings in the "continuous improvement" phase of low performers in the "understanding" phase

Table AIV. Mean cost savings in the "continuous improvement" phase of low performers

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