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The Influence of Cognitive Biases in Production Planning and Control: Considering the Human Factor for the Design of Decision Support Systems

Julia Bendul and Melanie Zahner

Abstract

Production planning and control (PPC) requires human decision-making in several process steps like production program planning, production data management, and performance measurement. Thereby, human decisions are often biased leading to an aggravation of logistic performance. Exemplary, the lead time syndrome (LTS) shows this connection. While production planners aim to improve due date reliability by updating planned lead times, the result is actually a decreasing due date reliability. In current research in the field of production logistics, the impact of cognitive biases on the decision-making process in production planning and control remains at a silent place. We aim to close this research gap by combining a systematic literature review on behavioral operation management and cognitive biases with a case study from the steel industry to show the influence of cognitive biases on human decision-making in production planning and the impact on logistic performance. The result is the definition of guidelines considering human behavior for the design of decision support systems to improve logistic performance.

Keywords: cognitive biases, human behavior, production planning and control, PPC, system design

1. Introduction

While in the area of psychology, anthropology, and sociology human behavior has been investigated intensely and although behavioral aspects became an integral part of economic research [1], in the field of logistics and production planning and control (PPC), only little research has been conducted [2]. In order to support decision-making processes in PPC and to optimize logistic performance, various models have been developed in order to reach short lead times, high due date reliability, low inventory levels, and high-capacity utilization as the key logistic performance indicators for production systems [3]. However, the underlying proposition of these models is typically the theory of the “homo

economicus.” In other words, to apply these models properly, we assume a fully rational human behavior in the decision-making process determined by the purpose of the decision-maker to maximize the personal advantage [4]. Tversky and Kahneman [5] challenged this assumption and showed that human decisions are biased, which means a systematic deviation from rational judgment. In the fields of logistics and PPC, people are often confronted with uncertainty and high complexity, and research has shown that under these framework conditions, humans systematically take wrong decisions [6]. One example for a complex situation in which biased decision-making leads to a deteriorating logistic performance is the so-called lead time syndrome (LTS). Here, production planners overreact to decreasing due date reliability. The planners adapt standard lead times too often, which eventually leads to an even worse aggravation of due date reliability [7]. To support this variety of decisions, which have to be made in PPC, the so-called decision support systems (DSSs) are used frequently. DSSs are computer-based information systems with the purpose to improve the decision-making process and its outcome [8].

In this chapter we aim to improve the understanding of the role of cognitive biases in the field of PPC and propose first design guidelines for decision support systems (DSSs). Therefore, we combine a systematic literature review on behavioral operation management and cognitive biases. Taking inspiration from a case study from the steel industry, we show the possible impact of cognitive biases on human decision-making in PPC and on logistic performance. The remainder of this chapter is structured as follows. In Section 2, we outline the typical decision-making processes and the corresponding DSS in PPC. In Section 3, we use the case of the PPC at a steel manufacturer to present several examples of the possible impacts of cognitive biases on PPC decision-making. In Section 4, we give first recommendations on how to avoid the emergence of cognitive biases within PPC decision-making and derive first guidelines for DSS.

2. Decision-making and decision support systems in PPC

2.1 Decision-making in operation management

Already in the 1980s, the *decision-making* has been recognized as a field of central research interest in the area of operation management [8]. Decision-making can be defined “[...]as the process of selecting the course of action that best meets the decision criteria, subject of the constraints inherent in the decision-making situation (DMS).” [9] p. 324.

According to [8] the DMP contains three phases. In the first “intelligence” phase, the problem which requires a solution by the decision-maker is identified and prioritized. Moreover, the first target achievements are defined, and corresponding data gathering is initialized. In the second “design” phase, a general action plan, which contains several action alternatives and their expected outcomes as well as the first evaluation criteria, is defined. In the third “choice” phase, the decision-maker selects the best action alternative based on the evaluation of each alternative. Based on the early works of [8], several models have been developed in order to explain the DMP. For instance, several authors suggest an extension of [8] DMP model [9, 10]. They propose a fourth “implementation” phase in which the decision outcome is turned into practice. In a fifth “learning” phase, lessons learned are formulated and shared in the organization to improve the DMP and the decision outcome in the future.

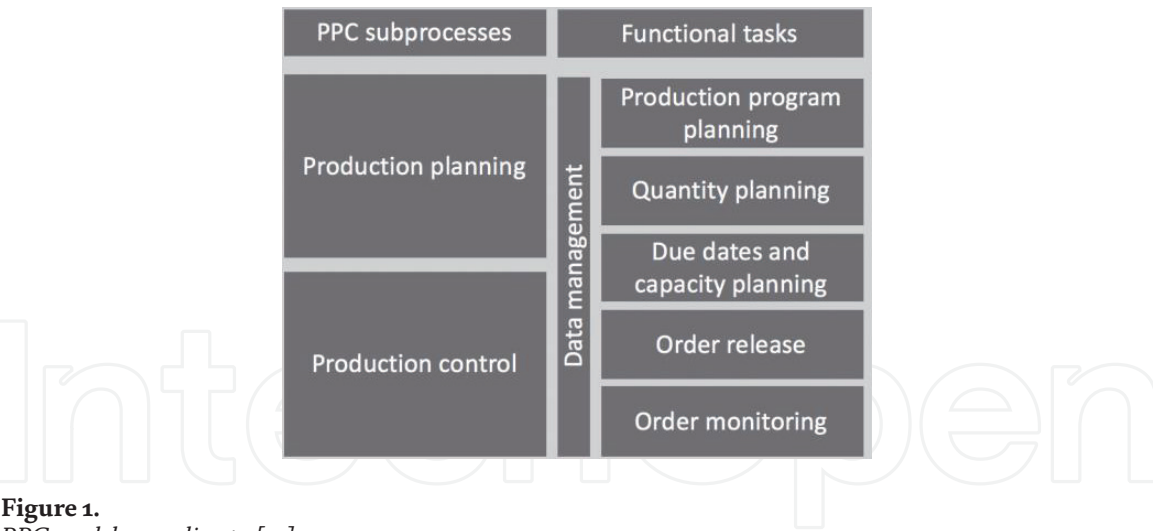


Figure 1.
PPC model according to [11].

2.2 Decision-making in production planning and control

Moreover, also, within PPC human decisions undergo the suggested phases of the DMP models. Typical decision-making situations of PPC are shown in **Figure 1**. PPC contains two subprocesses which are production planning and production control. These two subprocesses contain several task functions which require several decisions. Production planning focuses on the development of the basic concept to determine when to produce what in which quality. Production control has an overall monitoring function to achieve the production targets by the use of different control techniques.

Production program planning encompasses several decisions about the production sequence and the required materials. Based on this, *quantity planning* determines production quantities and lot sizes. *Due dates and capacity planning* contain several decisions concerning capacity plans and due dates for specific production steps. The *order release* marks the starting point for the production. Since disturbances, such as machine breakdowns, delays in material supply, or quality problems, may occur during production, a continuous *order monitoring* is accomplished. The necessary decisions within these main tasks of PPC are often complex and require the consideration of several parameters. Thus, in PPC typically decision-making is usually supported by DSS. DSSs are often self-developed by using case tools like Crystal, Analytica, or iThink for the development.

2.3 Insufficient design guidelines for decision support systems

While there is a lot of research on DSSs in general (e.g., [12]), as well as on several components and modules of DSS (e.g., [13]), there is only little research about standardized design guidelines for DSS. For instance, [6, 9] criticize the lack of an integrated framework to support a standardized design of DSS. However, [9] propose a framework as the basis for standardized guidelines for DSS designers.

Figure 2 shows the framework suggested by [9]. The framework contains four levels. (1) The first *decision-making level* is based on the original DMP model of [8] and on its extensions containing all five steps within the decision process. (2) The second *decision service task level* focuses on tasks which require human intelligence and is based on a task-method-subtask structure to infer logical conclusions from the analyzed data. (3) The third *architectural capability level* considers user interface, data information knowledge, and processing capabilities. (4) The fourth *computational symbol-program level*

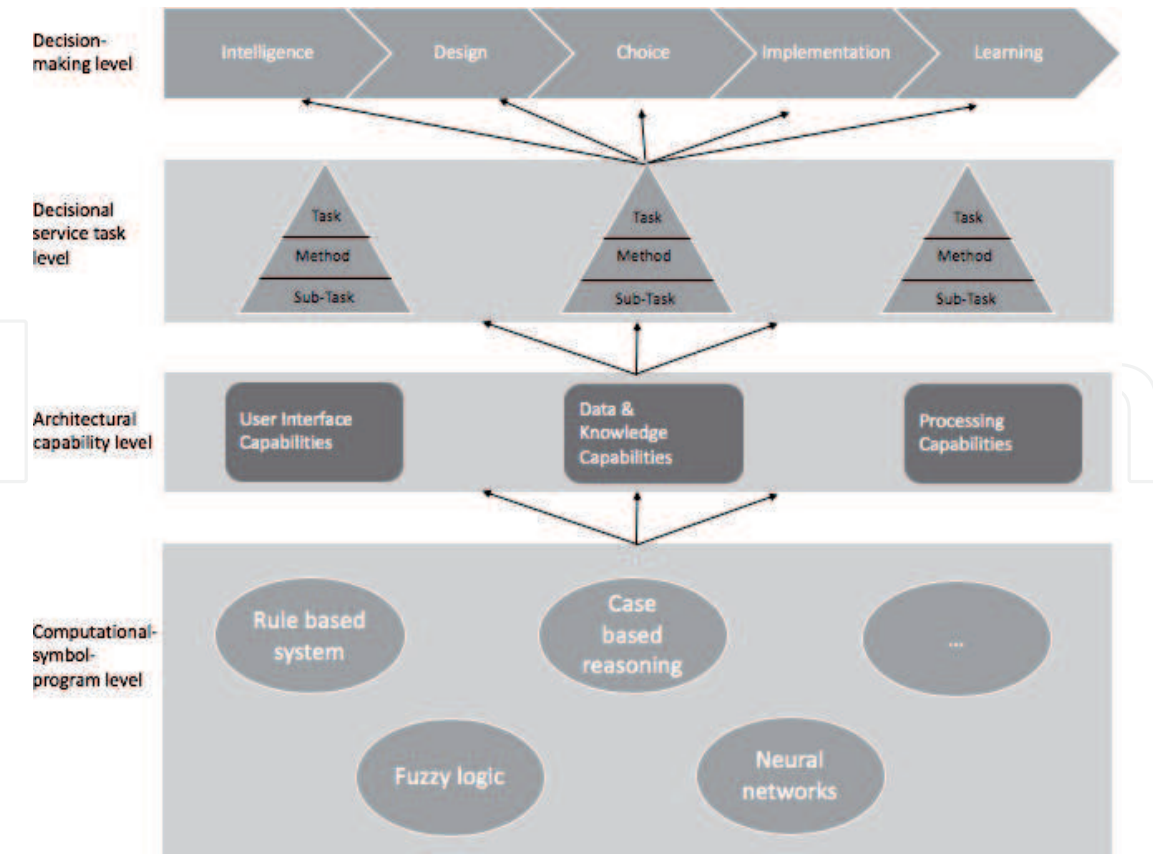


Figure 2.
DSS design framework with adaption according to [9].

focuses on specific computational mechanisms based on artificial intelligence techniques such as computer-based reasoning (CBR), rule-based system (RBS), etc.

3. Cognitive biases in production planning and control: the case of a German steel producer

3.1 Foundations of research on cognitive biases

Tversky and Kahneman [5] were the first who questioned the assumption of rational human behavior and introduced the term of cognitive biases. They state that humans taking decisions systematically go wrong, especially in complex and uncertain environments. In further experiments, [14] deepens this research of the underlying factors and describes the cognitive processes of intuition and reasoning.

Stanovich and West [15] named these cognitive processes System I (intuition) and System II (reasoning). While System I acts automatically, fast, emotively, and effortlessly and is hardly controllable, System II operates relatively slowly, reflected, and effortful [15]. System I creates spontaneous impressions and persuasions, which form the basis for further decisions and actions of System II. Based on this two-system view, [14] claims that impressions are generated in System I and judgments are made in System II.

This fundamental research made clear that there are plenty of different cognitive biases that may affect human decision-making. Ref. [6] categorized these biases into six main categories:

1. Memory biases describe biases influencing the storage and the ability to remember information.

2. Statistical biases are the human tendency to over- or underestimate certain statistical parameter.
3. Confidence biases act to increase a person's confidence in their prowess as a decision-maker.
4. Adjustment biases describe the human tendency to stick to the first available information or to a reference point when making decisions.
5. Presentation biases influence humans in their decision-making by the way how information is being displayed.
6. Situation biases describe the way how a person responds to the general decision situation.

3.2 Case study: decreasing due date reliability at a German steel producer

3.2.1 Initial situation

We take inspiration from a case study of the steel industry presented by [2]. The analyzed PPC process takes place within a R&D department of a German steel case company. To compete in the global steel market, a short time to market is crucial. Especially in the R&D department, production and analysis processes are hardly to plan, and it is one of the major challenges of production planners to fulfill the customer requested delivery date. Samples of new alloys have to pass sequences of different tests before they can be launched in the market. In the analyzed R&D process, the first orders for different steel samples are placed through external and internal customers. After estimating the planned lead time for several manufacturing and analysis processes, the orders get a due date. For the scheduling of the production orders, a custom-developed DSS is used. In total, a production system with 20 machines and 35 employees in 1 shift was analyzed over a period of 3 years (from 2011 to 2014, 1.023 orders were analyzed). On-site visits, expert interviews, and observation documents were the used research methods. To evaluate the key performance indicator (KPI) development in terms of due date reliability, inventory, and lead times, feedback data from 13 months based on 240 shop floor calendar days were analyzed.

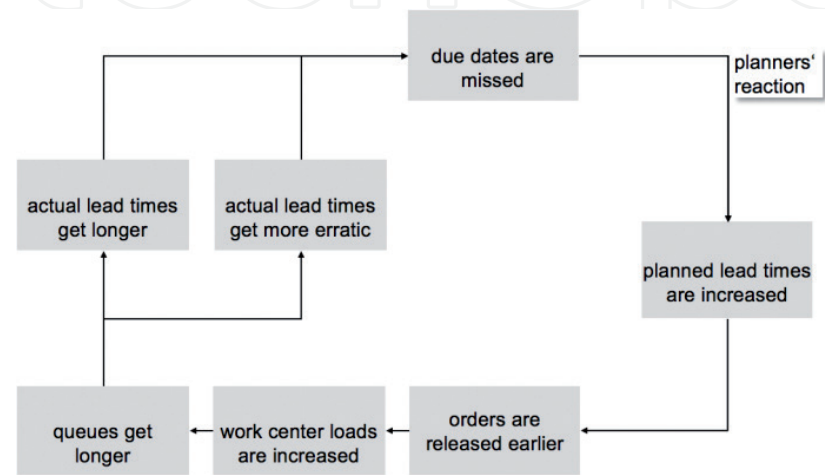


Figure 3.
Lead time syndrome in PPC.

3.2.2 Observed behavior of key performance indicators

The due date reliability was one of the key performance indicators, and 95% was set as a long-term target for the planners. We observed the so-called lead time syndrome active in this context. When planners recognized decreasing delivery reliability, they started to update the initially planned lead times by releasing waiting orders earlier and adding some additional safety lead times in that cases in which the initially lead time was too short to meet the target due date. Thus, more orders are in the production system which causes an increasing WIP level and growing lead times. As a result, the delivery reliability was even lower than before the update of the lead times. The planners feel pressured to improve the current situation, and the circle of updating lead times reinforces, resulting in an even stronger due date aggravation.

Figure 3 shows the process of the observed planner's behavior.

3.2.3 Observed behavior of planners: cognitive biases underlying deteriorating due date reliability

We observed several active cognitive biases in various decision-making situations in several PPC tasks. Nevertheless, it is important to understand that this classification of biases is not as concrete in practice as described in theory. Some of the cognitive biases overlap and often occur in several different situations.

3.2.3.1 Memory biases

Memory biases summarize a group of cognitive biases which are related to the storage and availability of information. The *availability heuristic* describes the tendency of people to overestimate the likelihood of events for which they can easily restore the information [14]. As a result, people tend to overweight the outcome of the last decision as a basis for their decision-making in their current situation. The *imaginability bias* describes the fact that people assume an event to be more probable if it can be easily imagined by themselves [16].

We observe that planners tend to adjust planned lead times based on their intuition instead of entirely considering all influencing variables.

This occurs mainly in the phase of the *production program planning* and *due date and capacity planning*. The planners tend to connect their last updates of the planned lead time to any positive development of the logistic performance. In case of a negative development, the planners assume that external influences such as a delay in material delivery or machine failures are responsible for the fact delayed due date reliability. They conclude that there is a need for another planned lead time adjustment.

We observe the same development for the *production program planning*. In the cases when the defined production sequence leads to a positive performance outcome, the planners relate this development to the quality of their own planning capabilities. In those cases when the defined production sequence leads to a decreasing due date reliability, the planners connected this with external influencing factors and conclude a necessary update on the production sequence, even though this was not optimal for the current situation.

3.2.3.2 Statistical biases

Statistical biases describe the tendency to over- or underestimate certain statistical parameters. Ref. [14] investigates that humans tend to overestimate the probability of two events occurring together if this has already happened once in

the past. This effect is described by the *correlation bias*. For example, a change in material and an increase in lead times for a certain machine can lead to the assumption that there is a correlation between this material change and extending lead times—which actually does not exist. The *gambler's fallacy* describes the phenomenon of the assumption that future events are determined by the occurrence of past events [17]. This leads to an overestimation of possible events ignoring the actual statistical possibility [18].

We observe statistical biases in the adaption of lead times within the *phase of the order monitoring*. The planners tend to assume that the coincident adaption of planned lead times and the positive development of due date reliability are correlated, although they are aware of the mathematical fact that it takes 4 weeks until the adaptation of planned lead times will become visible in an improved due date reliability.

We observe these biases also in the *phase of production quantity planning and the order release*. Delays in material provision and machine breakdowns which occurred at the same time lead to the assumption that there is a possible correlation and that this may also increase the system's scrap rate. However, the planners do not further validate this assumption, and the planners simply increase the material orders to reach the desired production output. As a result, the inventory level increases excessively, since the additionally ordered material cannot flow off because the assumed correlation was not true.

3.2.3.3 Confidence biases

Confidence biases describe the set of biases concerning the person's confidence in their prowess as a decision-maker. The *illusion of control or overconfidence biases* describes the tendency of people to overestimate their ability to solve difficult problems [19]. The *confirmation bias* leads people to seek for information which confirms their own estimation and hides information which is contrary to their own perception [20].

Analyzing the case study, we find three examples of the *illusion of control* in the *phase of due date planning*. (1) Planners tend to assume that their own procedures are more suitable than the standard planning procedures. (2) When planning the lead times, they behave as if the stable forecast of future incoming orders is predetermined and not only a prediction. (3) Planners increased the WIP level via the planned lead times in order to avoid the production system to run into an idle state. We also found situations exemplary for active confirmation biases. Planners let themselves be guided by their intuition: if planners *feel* that updating the lead times would be the best option to increase due date reliability, they search particularly for information which confirms this feeling. Obvious information which entails the result not to intervene in the planned lead times (such as the given *planning rules* that limit the number of planned lead time updates within a certain period of time) is ignored.

Confirmation biases were also observed in the phases of *production program planning* and *production quantity planning*. Planners behave as if the estimated future customer demand forecasts are stable and the demand numbers are already fixed. Accordingly, they ordered the corresponding materials and plan production sequences without any buffers accordingly. Moreover, we notice that even when the customer demand is in the course of time and can be determined more specifically (no matter whether it is higher or lower than previous forecasts), planners seek for information which confirms the first numbers in order to justify that they stick to their initial plan (e.g., they search for cases in which certain customers have increased order quantities at first and then lowered them).

3.2.3.4 Adjustment biases

Adjustment biases describe the human tendency to stick to the first available information or to a reference point when making decision. The *anchoring effect* is defined as the tendency to rely on an initially given information too heavily—which influences further values [5]. Teng and Das [21] show that anchoring can create systematic errors in decision-making situations. Adjustment biases also include *conservatism bias*. Similar to the anchoring effect, taken estimations are not updated according to new information [22].

This became obvious in the phase of the *order release* and *order monitoring* in the context of lead times. We find that lead times from previous years and from similar work systems act as anchors. When setting planned lead times, planners justify the extension of planned lead times with the numbers in the year 2014. Similarly, the planners tend to aim at a due date reliability of 95%, which is given as the long-term goal (but which is far from reality), and therefore seem to extend the planned lead times disproportionately.

The same effect becomes obvious for the capacity planning. The planners justify their machine capacity planning with target figures of machine utilization rates of the previous years. These figures were not updated to the current situation.

3.2.3.5 Presentation biases

Presentation biases summarize a set of cognitive biases which influence humans in their decision-making by the way how information is being displayed. The *ambiguity effect* describes the human tendency to favor simple-looking options and avoid options that seem to be complicated [23]. According to the *primacy/recency effect*, information at the beginning and at the end of a series can be restored best, whereas information in the middle are restored worst [24].

The implemented DSS offers plenty of types of analysis (such as the order forecasts, inventory levels, etc.) next to the information which is central for setting planned lead times. The *primacy recency effect* became obvious in the phase of order monitoring when the planner was setting the planned lead time for a certain order to the double value of what was reasonable. This is because he had just checked the current due date reliability and noticed that the value for the previous day was particularly low.

Further, we identified the influence of the ambiguity effect in the material quantity planning. When planners recognized that the production could run out of material, they just increased the initially ordered quantity. They did not further analyze potential causes like an increasing scarp rate due to an incorrectly set machine, etc. Instead they took the simplest option right in front of them to keep the production running even though the failure cause exponentiated.

3.2.3.6 Situation biases

Situation biases describe the way how a person responds to the general decision situation. The *complexity effect* describes that people are biased under time pressure or when information overload occurs [25]. The *ostrich effect* describes the habit of people to ignore an obvious negative information [26]. The *bandwagon effect* describes the tendency to do things because many other people do the same [4].

We identify situation biases in several tasks in PPC. Modern PPC DSSs provide a wide range of information, such as key performance indicators concerning delivery reliability, inventory levels, or throughput times. For many planners, the amount and variety of information are too much to be included in their

	Memory Biases	Statistical Biases	Confidence Biases	Adjustment Biases	Presentation Biases	Situation Biases
Production program planning	▪ Availability heuristic ▪ Imaginability bias		▪ Illusion of control ▪ confirmation bias			▪ Complexity effect ▪ Bandwagon effect ▪ Ostrich effect
Quantity planning		▪ Gambler's fallacy ▪ Correlation bias	▪ Illusion of control ▪ confirmation bias		▪ Ambiguity effect ▪ Primacy recency effect	
Due dates and capacity planning	▪ Availability heuristic ▪ Imaginability bias		▪ Illusion of control ▪ confirmation bias	▪ Anchoring effect ▪ Conservatism bias		▪ Complexity effect ▪ Bandwagon effect ▪ Ostrich effect
Order release		▪ Gambler's fallacy ▪ Correlation bias		▪ Anchoring effect ▪ Conservatism bias		
Order monitoring		▪ Gambler's fallacy ▪ Correlation bias	▪ Illusion of control ▪ confirmation bias		▪ Ambiguity effect ▪ Primacy recency effect	▪ Complexity effect ▪ Bandwagon effect ▪ Ostrich effect

Figure 4.
Observed cognitive biases in the case of steel production PPC.

decision-making. In particular, under time pressure the planners decide to extend lead times just to do anything, even when they do not come to a reasonable conclusion when analyzing the data. At the same time, the planners ignore the fact that their own behavior of extending lead times influences due date reliability in a negative way. Moreover, we find that adjusting lead times is a common method of reacting to decreasing due date reliability. Planners who face the situation of decreasing due date reliability choose planned lead time extension just because their colleagues do so. Also, in the case of a machine breakdown, a similar behavior could be observed. The closer the delivery due date, the more planners decided to switch machines and change the production program sequence just to do anything. This was even true when the effort and time to change machines take in total longer than the repair of the initial machine.

Figure 4 shows a summary of our observed cognitive bias categories within the several PPC tasks. Potentially, there are even more active biases in the several PPC tasks, which we did not observe in our case.

4. Debiasing by the design of decision support systems

DSSs intend to improve the decision outcome by supporting the human decision-making process [6]. Therefore, in the design of DSSs, also human behavioral aspects need to be considered to get an unbiased decision outcome. Based on our identified cognitive biases in PPC decisions, we aim to give first recommendations for system developers of DSS.

The proposed framework of [9] serves as the basis and is extended by a so-called behavioral layer. In this, already in the design phase, the DSS should foresee adequate *debiasing techniques* to support planners properly and thus to positively affect logistic performance of the production system.

Debiasing is a method to reduce or eliminate the influence of cognitive biases within the decision process. Keren [27] proposed the following three steps for effective debiasing:

1. Identification of the existence and nature of the potential bias and the underlying influencing factors
2. Consideration of ways and techniques to lower the impact of bias
3. Monitoring and evaluation of the effectiveness of the selected debiasing technique

The proposed steps should be included in the design of a DSS. Based on our findings about the active cognitive biases in PPC, we already fulfilled the first step. In this section we contribute to the second step and aim to propose ways and techniques to lower the impact of biases. The third step then needs to be analyzed and observed over time.

These steps form the generic basis for a debiasing approach which contains further debiasing categories describing the concrete method of debiasing.

Kaufmann et al. [28] propose five categories for effective debiasing strategies in supplier selection processes:

1. Decomposing/restructuring
2. Put yourself in the shoes of
3. Draw attention to alternative outcome
4. Devil's advocate
5. General bias awareness

We used these categories as a basis for the development of the first design guidelines for DSS in the field of PPC.

(1) Decomposing/restructuring: By applying this method, the decision and the related information are restructured and separated to match the task and the capabilities of the decision-maker [29]. Therefore, decisions, such as production program planning within PPC, should be split into single tasks. In other words, the production program planning should be broken down into the subtasks of the decision about the production of several product categories, the corresponding quantities, and the due dates. In order to avoid an information overload for the DSS user and the occurrence of the situation biases (which may cause losing the overview of the connection between single parameters), the DSS should only show the most relevant information for a decision. Additional parameters should be available in the system in the background and should be provided upon request. For example, a machine breakdown can entail a decision update on the capacity planning because the production quantity originally planned on the broken machine has to be switched to another machine. Occasionally, this can also result in a necessary update of the production program. If this is the case, only in the moment when a decision becomes relevant, the request should be provided.

(2) Put yourself in the shoes of: The objective of this method is to enable the decision-maker to consider all the influencing parameters of affected parties through a perspective shift [28]. To enable this method, a pre-analysis of the affected stakeholders of potential decision cases is required.

Within the DSS this method can be applied in two ways. (1) First, before making a final decision, potential scenarios can be presented to the decision-maker. This should also include the implications for logistic performance (e.g., inventory levels, lead time, due date reliability). For example, the implications of a change the production program may have for machine and personnel capacity as well as for material requirement planning should be made visible to the planner even if these implications are only of interest for other departments (e.g., the logistics and the purchasing department). (2) Second, historical data on the decision-making and the outcomes in terms of logistic performance can be provided (e.g., the decision about the lead time in the previous month caused this delivery reliability).

(3) Draw attention to alternative outcome: This method focuses on alternative outcomes to avoid the confirmation biases seeking for supportive information on the initial hypotheses. Thinking about counter explanations as well as the opposite intention and perspective can broaden one's own decision-making horizon. For example, in the case of a machine failure, the first intention of planners in our observed case was to switch the machines to stick to the production due date. However, this caused additional setup time. The opposite intention here would be to stick to the initial planned machine and wait for the machine to be repaired or start with some tasks which can be done without the machine to avoid losing time due to the machine breakdown and avoiding additional setup time at the same time.

(4) Devil's advocate: This debiasing strategy focuses on the possible critique of other parties affected by the taken decision. Thereby, the *devil's advocate* argues against the position of the decision-maker. Through this presentation of a formalized dissent, the decision-maker is forced to proof his decision and find supportive arguments. Research has shown that this leads to better solutions [28, 30]. An important criterion to apply this method successfully is that the devil's advocate is nonemotional in raising his dissent [31]. Therefore, including this method in a DSS is appropriate to fulfill this criterion. Before executing the final decision regarding the extension of a planned lead time, a pop-up window should arise and present a summary of all possible negative effects linked to the question whether the decision-maker is sure about continuing with his decision. Exemplarily, in a case of intended machine switch which also causes setup requirements for tooling, etc., the system should ask whether this really should be done.

(5) General bias awareness: The general awareness of the existence of cognitive biases can be understood as an overall debiasing strategy. Even if the general understanding of the underlying influencing factors on decisions can improve decisional judgment quality, it cannot completely eliminate its emergence [32]. A wider understanding of the influence of cognitive biases on decision-making can be achieved, for example, by provision of short training videos or a user tutorial explaining the influence of cognitive biases. This can be the starting point before using the DSS tool initially. The *general bias awareness* can also be affected by the layout of the graphical user interface as well as by the structure of the DSS which should be well organized and intuitively understandable. This contributes to the avoidance of *situation biases* due to an information overload. Moreover, in attention to the *statistical and the anchoring biases*, just presenting simple figures should be avoided, and additional context information should be added. Based on our observed case study of the long-term target delivery reliability of 95% which acted as an anchor and was quite unrealistic, it would be better to give additional information such as a delivery reliability target for each month and more content information about corresponding developments such as an allowed inventory level or machine utilization rate to achieve this goal.

Figure 5 shows our proposition for a further design layer for the DSS design framework presented by [9].

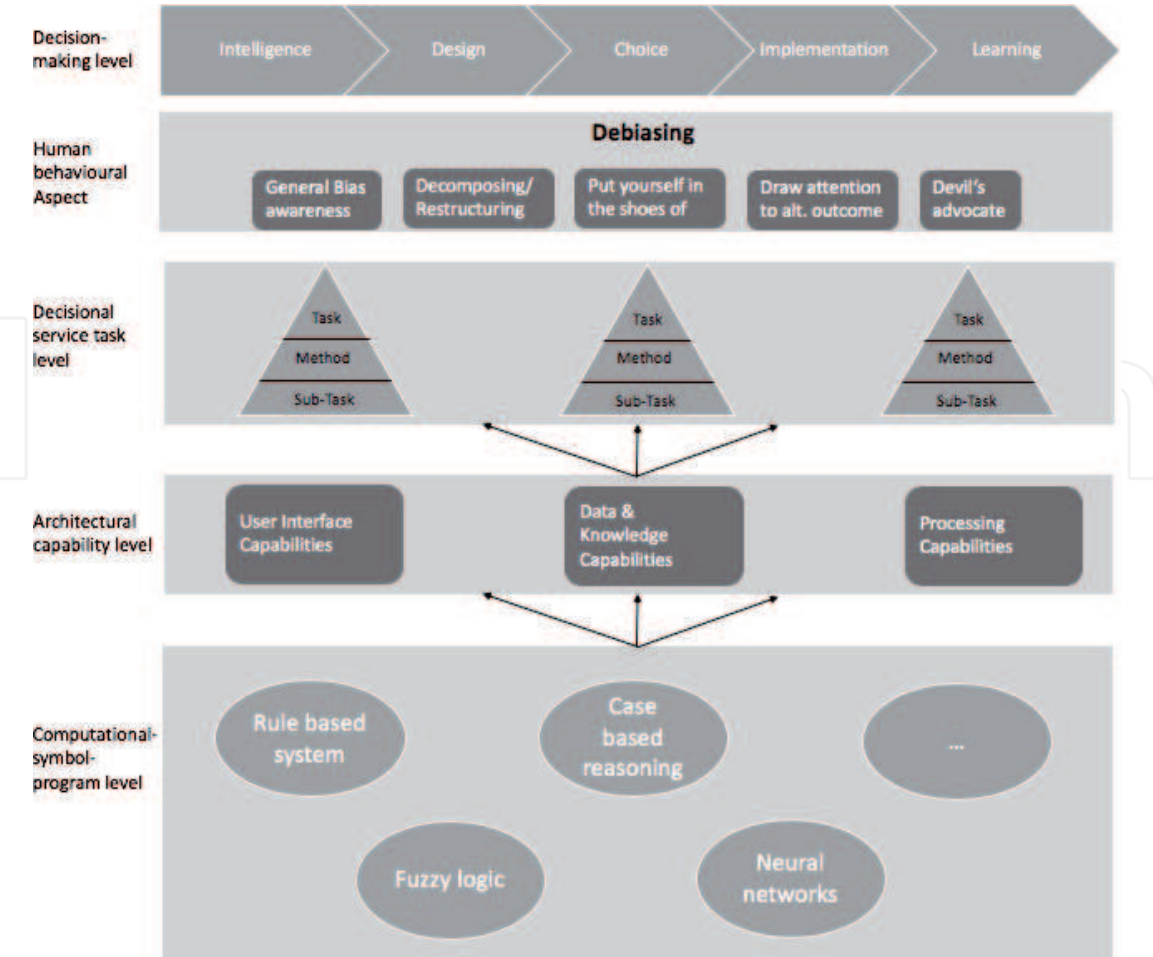


Figure 5.
DSS design framework presented by [9] with our proposition of an additional layer for the DSS design framework.

5. Conclusion

Behavioral aspects in operations management have been investigated for several years. We contribute to this research stream by analyzing the meaning of cognitive biases for decision-making in the field of PPC. The aim of this chapter is to determine first design guidelines for DSS considering the behavioral factors influencing human decision-making. The presented case study shows this need for industrial practice. Frameworks that aim to give advice to designers of DSS ignore the importance of the human factor in decision-making. We contributed to this research by extending the proposed design framework of [9] by adding the human behavioral layer. Moreover, we show first possible design techniques for DSS considering debiasing methods especially for decisions in PPC.

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