The Role of Human Factors in Production Networks and Quality Management

Ralf Philipsen[1], Philipp Brauner[1], Sebastian Stiller[2], Martina Ziefle[1], and Robert Schmitt[2]

[1] Human-Computer Interaction Center (HCIC)
[2] Laboratory of Machine Tools and Production Engineering (WZL)
RWTH Aachen University, Germany
philipsen@comm.rwth-aachen.de

Abstract. Quality management in production networks is often neglected. To raise awareness for this subject, we developed an educational game in which players are responsible for managing orders and investments in quality assurance of a manufacturing company. To understand individual performance differences and playing strategy, we conducted a web-based study with 127 participants. Individual performance differences were discovered. Players who closely observe the company data and frequently modify order levels and quality investments perform significantly better. Furthermore, we found that the game model works and that the awareness towards quality assurance increases through the interaction with the game. Hence, the game is a suitable educational tool for teaching decision making in quality management.

Keywords: Quality Management, Decision Support, Human Factors, Production Networks, Personality Traits, Game-based Learning.

1 Introduction

Many of today's products are built from a large number of components that are delivered by a number of different suppliers. To enable a company to profitably manufacture its products, an efficient and viable production network is required. However, in today's globalized world these networks have reached a very high complexity [1]. Decision makers in current production networks need to have a comprehensive overview of the interrelationships of their company, the suppliers, and customers of many of different products and components. The arising problems are twofold: Not only do the decision makers have to ensure that enough components are available in the production process, but also a sufficient quality of the components has to be assured.

Modern Enterprise Resource Planning systems support people in their decision making. However, the huge quantity of presented and retrievable information might lead to information overflow and users who might focus on the wrong parameters, leading to inefficiencies, low product quality, or lower profits in the production networks. Human behavior in production networks and quality management is insufficiently explored. In order to study decision making processes in quality management

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and to develop tools that can give suitable support to decision makers, we developed a web based simulation that puts users into the role of decision makers.

This publication serves a dual purpose: First, we present the design and implementation of a simulation game for quality management in production networks. Second, we analyze the effect of human behavior and characteristics in the developed game as well as the consequences for real world companies.

2 Development of a Game for Quality Management

Simulations are experiments within a controlled environment, thereby reducing aspects of the real world in terms of structure and behavior. The behavior of complex systems is neither predictable nor completely understandable. The combination of human intuition and analytical modeling is utilized as a model for decision making in complex systems such as production and supply chain networks [2] [3] [4].

In order to train and support decision making, simulation models and serious games serve as ideal training environments, in which managers are confronted with challenging situations that require fast and important decisions. These games support the awareness of typical problems in production, logistics, or quality management, e.g., the Beer Distribution Game, Goldratt's game [5] [6], KANBAN simulations. However, no games exist that address quality management in production networks.

The Quality Intelligence Game (Q-I Game) is a turn-based game in which players have to fulfill the customer demands by procuring and processing vendor parts into a given product. In contrast to the Beer Distribution Game, players also have to take quality aspects into account. Studies suggest that quality management influences profit in two different ways: First, good quality management increases company profits through higher product quality, resulting in higher customer satisfaction and larger sales volumes. Second, process optimization as a part of quality management leads to lower variable and fixed costs. Therefore, a trade-off between product quality and its costs is required [7].

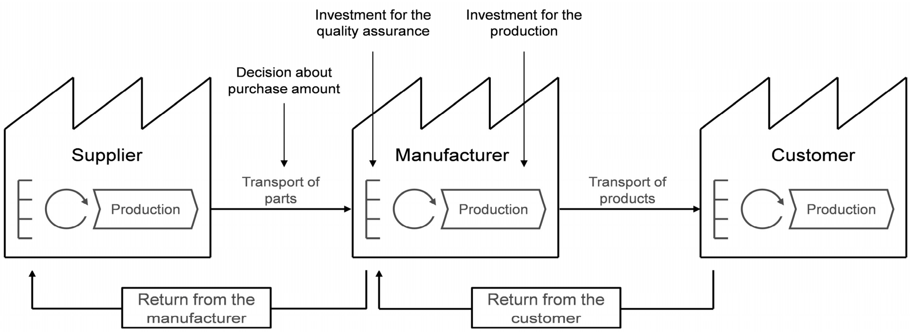

Fig. 1. Principle of the Q-I-Game

The Q-I game model is designed around three pivotal decisions (see Figure 1 for a schematic representation). First, players have to invest in the inspection of incoming goods. Second, players need to control the investments in their company's internal production quality. Third, similar to the Beer Distribution Game, players need to manage the procurement of vendor parts. The players have to find an optimal trade-off between these three dimensions in order to make the highest profit. The influences of these dimensions on the company's profit are explained in the following.

The first dimension contains the inspection planning and control of supplier parts, including complaint management between the manufacturer and his supplier.

Inspections at goods receipt can cause an ambivalent behavior of quality and production managers. While the inspection itself is not a value-adding process and hence a driver of variable and fixed production costs, inspections give the managers the opportunity to protect their production systems from faulty parts and goods. Also, it facilitates the supplier evaluation and development since the quality of supplied parts and goods is measured.

The production quality dimension is taking the production and final product quality of the manufactured goods into account. Investments in production quality will increase costs, but it will decrease the number of customer complaints.

To assure a continuous production, the player has to procure necessary parts from its supplier. Contrary to the Beer Distribution Game, the customer demand is kept constant within the Q-I game, in order to leave the focus on the decisions of quality management. Nevertheless the player has to consider scrapped parts due to low production quality or blocked parts due to poor supplier product quality in their orders.

The Q-I game gains complexity through the introduction of random events. First, the quality of the vendor parts can change drastically. Second, the internal production quality can change. Possible reasons are broken machines, better processes, failures in the measurement instruments, etc. Third, the customer demand may shift.

3 Evaluation of the Q-I-Game

After implementing the Q-I-Game with Java EE 7, it was used in a study to validate the game model and research possible effects of human factors on players' performances within the game. In the following sections, we present the defined variables, the experimental setup, and the sample of the study.

3.1 Independent Variables

In order to understand how decision making in quality management is influenced by human factors, several demographic data and personality traits were gathered. Age, gender and educational qualifications were collected as independent variables. In addition, participants were asked to assess their previous experiences with quality management, production management, supply chain management, logistics and business studies. Furthermore, we measured the technical self-efficacy with Beier's inventory [8], a method already proven to show performance in computer-based supply-chain-management simulations [9]. In order to analyze potential effects of personality, we used a version of the five factor model shortened by Rammstedt [10] to identify the participants' levels of the personality traits openness, conscientiousness, extraversion, agreeableness and neuroticism. Furthermore, previous studies revealed that performance regarding supply chain management was affected by their risk-taking propensity; therefore, we used the "General Risk Aversion" inventory by Mandrik & Bao [11] as well as the "Need for Security" inventory by Satow [12] to measure the participants' willingness to take risks. Xu et al. showed that the personal attitude towards quality contributes to Total Quality Management practices [13]; therefore, we measured the quality attitude with a newly constructed Quality Attitude Inventory, which consists of 8 items. 6-point Likert scales were used for all measurements.

3.2 Experimental Variables

In order to analyze the effects of complexity on players' performances, we implemented two in-game events to vary the degree of difficulty. One was a potential spontaneous drop of the supplier's quality by 30% in the tenth month. The other was a possible drop of the internal production quality in the same month. The occurrence of both events was fully randomized between both the participants and the two rounds played by each player.

The availability of quality signal lights was varied as a within-subject variable; accordingly, all participants played one round with and one without the signal lights. Whether the lights were shown in the first or the second round was randomized.

3.3 Dependent Variables

Detailed logs of investments, incomes, costs and profits of each simulated month were used to analyze the players' behaviors within the game. The achieved profit was used as the central measure for the players' performances. In addition, several information about the players' interactions with the game were recorded: duration of reading the instructions, time to complete a month as well as a round, the number of help accesses and the number of adjustments to investments and orders.

3.4 Ranking Tasks

In addition, the participants were asked to rank factors of data provisioning and corporate strategy according to their importance for a successful performance in the game and for an economical production. They were asked to perform these tasks both before and after the game to discover possible effects on participants' opinions caused by playing the game.

3.5 Experimental Setup

The experimental setting consisted of our web-based quality management simulation, which was embedded between the pre- and post-part of an online survey. Announcements on bulletin boards, social networks, emails and personal invitations were used to recruit participants for the study. Each had to play 2 rounds of 24 month each. 219 people started the online pre-survey, 129 played both rounds of the game and finished the post-survey. The obtained dataset was revised to eliminate players who did not play seriously, i.e. who placed excessive investments or orders or did not change the settings at all. Therefore, two cases had to be removed for not performing any adjustment during both rounds. Accordingly, the final revised dataset contained 127 cases. Although the participants had to play 24 simulated month per round, only the data of up to and including month 20 were used in the analysis to exclude possible changes of players' strategies late in the game like emptying the warehouse completely.

3.6 Participants

97 (76.4%) of the participants were male, 30 (23.6%) were female. They were between 17 and 53 years of age. The mean (M) age was 27.7 years (SD 7.2 years). 58.6% (60) of the participants reported a university degree as their highest achieved level of education. 39.7% (50) participants had a high school diploma and 6.3% (8) had vocational training. The average level of previous experiences regarding the subject matter were rather high. 67.7% (86) had previous knowledge in quality management, 65.9% (83) in business studies and 57.5% (73) in production management.

The participants' average personality traits regarding the five factor model were comparable to the reference sample of Rammstedt [10] with the exception of a slightly lower level of agreeableness. The only significant difference between men and women regarding this model was found at the neuroticism scale ($F(1, 125) = 7.498$, $p = .007 < .05$*): men showed lower average levels ($M = 1.99$, $SD = 0.97$) than women ($M = 2.58$, $SD = 1.22$). In addition, gender related differences were found regarding all three inventories of needs (recognition, power, security) ($p < .05$* for all needs), technical self-efficacy ($p = .000 < .05$*), willingness to take risks ($p = .002 < .05$*) and performance motivation ($p = .000 < .05$*). With the exception of the need for security men showed higher average levels in all aforementioned scales. In contrast, there was no significant difference found regarding the attitude towards quality.

4 Results

The result section is structured as follows: First, we will present the impact of the game mechanics and instructions on the player's performance. Second, we will have a closer look at the impact of user diversity. Furthermore, we will present the effects of behavior and strategies within the game. Last, we will report the ranking task results.

The data was analyzed by using uni- and multivariate analyses of variance (ANOVA, MANOVA) as well as bivariate correlations. Pillai's trace values (V) were used for significance in multivariate tests, and the Bonferroni method in pair-wise comparisons. The criterion for significance was $p < .05$ in all conducted tests. Median splits were used for groupings unless the factor offered a clear dichotomy.

Unless otherwise described, the effects in the following are valid for both rounds of the game. However, for clarity reasons, only the effect values of the second round will be reported. All profit related values like means and standard deviations will be reported in thousands for similar reasons; for computations the exact values were used.

4.1 Effect of Game Conditions

As expected, the participants made the highest average profit (M = 148.5, SD = 128.0) on the condition that there was no spontaneous drop of supplier's and internal production's qualities during the game. The mean profit in games with a drop of supplier quality was only slightly lower (M = 132.9, SD = 81.2). In contrast, average profits were considerably lower (M = 11.5, SD = 236.8) with drops in either both supplier's and internal production's quality or in internal production's quality only (M = -1.3, SD = 316.4), as shown in Table 1.

Table 1. Achieved average profits under different game conditions

		Drop of supplier's quality	
		no	yes
Drop of internal production's quality	no	148.5	132.9
	yes	-1.3	11.5

A two-way ANOVA revealed that the drop of internal production quality had a significant effect on players' average profits (F(1, 122) = 12.342, p = .001 < .05*); in particular, players averagely performed significantly worse under game conditions containing the aforementioned drop. On the other hand, the spontaneous drop of supplier's quality had no significant influence on average profits.

With both possible quality drops controlled, the presence of signal lights had no significant effect on players' average profits (p = .537, n.s.). Also, the impact of signal light availability within any of the four possible game conditions resulting from quality drop combinations did not reach the criterion of significance. Both the presence of signal lights and the quality drops of supplier and internal production as experimental variables will be controlled in the computations of the following sections.

4.2 Effect of Repetition

There was a strong correlation between players' average profits in the first and in the second round (r=.730, p=.000 < .05*); accordingly, participants who achieved a high/low profit in the first round, on average achieved the same level of profit in the second round. Furthermore, players' mean profit increased significantly between the first (M = -19.0, SD = 258.5) and the second round (M = 76.6, SD = 218.3) with Pillai's trace value (V) = 0.23, F(1, 126) = 36.6, p = .000 < .05*.

4.3 Effect of User Diversity

Several aspects of user diversity have been studied for potential effects on players' performances within the game. First, male participants made a higher average profit (M = 104.9, SD = 187.1) than women (M = -14.7, SD = 282.5). However, the effect is only significant for the second round ($F(1, 124) = 7.160$, $p = .008 < .05$*), not the first round ($F(1, 124) = 3.235$, $p = .074$, n.s.). Second, there was no correlation between age and the player's profit ($r = .057$, $p = .553$, n.s.). Previous experiences did not influence the game performance, e.g., neither knowledge in quality management ($p = .087$, n.s.) nor business studies ($p = .070$, n.s.) had a significant effect on performance within the game with game conditions controlled. Although participants with a high level of domain knowledge performed better under game conditions containing the aforementioned drop of internal production's quality ($M_{2QM} = 86.8$, $SD_{2QM} = 150.3$) than players with low knowledge ($M_{2QM} = -59.5$, $SD_{2QM} = 333.8$), this effect was only significant in the second round of the game ($F(1, 58) = 4.928$, $p = .030 < .05$*).

In addition to the customary demographic data several personality traits were analyzed. First, none of the "Big Five personality traits" of Rammstedt et al. [10] impacted the players' performances significantly ($p > .05$, n.s. for all indexes). Second, and contrary to several previous studies, there was no significant relation between technical self-efficacy and achieved average profit ($r = .163$, $p = .084$, n.s.). Third, there was no effect of the willingness to take risks on players' performances. Neither the "General Risk Aversion"-index of Mandrik & Bao [11] ($r = -.174$, $p = .065$, n.s.) nor the "Need for Security"-index of Satow [12] ($r = .054$, $p = .573$, n.s.) correlated with the achieved profits. Moreover, the personal attitude towards quality did not correlate with participants' average performances within the game ($r = .109$, $p = .248$, n.s.).

4.4 Effects of Behavior within the Game

Two main factors were analyzed regarding the players' behaviors within the game. First, the duration of playing correlated with players' average profits in the first round ($r = .301$, $p = .001 < .05$*). Therefore, spending a higher amount of time for a game averagely led to significantly higher profits in the first round. However, the effect was no longer significant in the second round ($r = .142$ $p = .112$, n.s.).

Second, the number of adjustments correlated with players' performances ($r = .303$, $p = .001 < .05$*). Users who adapted their investments and orders frequently achieved higher mean profits. A per-month analysis revealed that the average number of adjustments made by participants who achieved a high profit exceeded the adjustments of low performers in every month, as shown in Figure 2. Moreover, there was a peak in high performers' adjustments in month 11 as a reaction to the spontaneous drops of the supplier's and/or the internal production's quality in month 10. This change in interaction between month 10 and 11 is significant for high performers ($V = .164$, $F(1, 62) = 12.140$, $p = .001 < .05$*). In contrast, there was no significant change in the adaption behavior of low performers at that time ($V = .001$, $F(1, 63) = 0.088$, $p = .768$, n.s.). Also, there is a medium correlation between the averagely performed adjustments in the first and the second round (r = .580, p = .000 < .05*). In particular, players who frequently/rarely adapted their investments and orders in the first round, acted similarly in the second round.

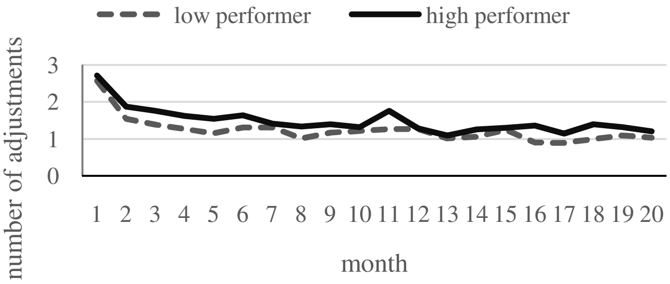

Fig. 2. Average adjustments per month of high and low performers in the second round

4.5 Effects of Strategy

There were several effects on players' performances regarding the used game plans. First, participants who assessed their behavior in the game as highly conscientious made a higher profit (M = 135.0, SD = 111.5) than those with low conscientiousness values (M = 38.4, SD = 261.1). This effect was significant (F(1, 123) = 4.987, p = 0.27 < .05*). Second, the stated level of forward planning in game strategy correlates with average profits (r = .184, p = .040 < .05*): Users who stated their strategy was dominated more by forward planning than by reacting, on average made higher profits. Third, the level of risk taking in the game plan negatively correlated with players' average performances (r = .-.217, p = .015 < .05*), e.g., players who claimed to have taken more risks than they would in real live made significantly lower profits. Also, there was a low correlation between participants' profits and the tendency to keep a small safety buffer of parts readily available (r = .273, p = .002 < .05*).

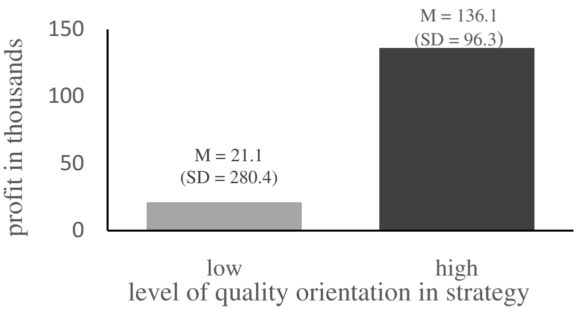

Fig. 3. Means (SD) of profit regarding strategies with different levels of quality orientation

Most of all, the level of quality orientation in players' strategies correlated significantly with the average performances (r = .370, p = .000 < .05*); therefore, participants with a quality-oriented strategy averagely performed better (M = 136.1, SD = 96.3) than participants who were inclined to ignore quality aspects (M = 21.1, SD = 280.4), as shown in Figure 2.

4.6 Requirements for an Economic Production

Participants averagely ranked "Increasing economic efficiency" as the most important requirement for an economic production (M = 2.1, SD = 1.3) before they played the game, followed by "Increasing quality of own production" (M = 2.2, SD = 1.1), "Increasing supplier's quality" (M = 3.3, SD = 1.1), "Optimizing stock" (M = 3.7, SD = 1.2) and "Decreasing delivery time" (M = 3.8, SD = 1.2). Although there is an absolute ranking, which results from comparing the aforementioned means, there is neither a significant difference between the first two ranks (p = 1.00, n.s.) nor between the ranks 3 to 5 (p > .05, n.s. for all comparisons). The positions of "quality of own production" and "economic efficiency" had been switched in post-game ranking, while there was no difference regarding the absolute ranks 3 to 5, as shown in Table 2.

Table 2. Ranking, means, and standard deviations of requirements for an economical production (left) and data requirements for successful performance (right) (ranked after playing)

Rank	Requirement	**M**	**SD**
1	Increasing quality of own production	1.8	0.9
2	Increasing economic efficiency	2.8	1.5
3	Increasing supplier's quality	2.9	1.2
4	Optimizing stock	3.3	1.2
5	Decreasing delivery time	4.2	1.1

Rank	Requirement	**M**	**SD**
1	High quality of data	1.8	0.9
2	Good data visualization	2.3	1.1
3	Decision support	2.8	1.2
4	High data volume	3.8	1.2
5	Low data volume	4.3	0.9

Pairwise comparison of all factors revealed that there is a significant difference between the average raking of "Increasing quality of own production" and all other factors (p = .000 < .05* for all comparisons). Similarly, the ranking of "Decreasing delivery times" averagely differs from each of the other factors with p = .000 < .05*. On the other hand, there was no significant difference between the rankings of the remaining items (2-4). In particular, while in pre-game ranking there were only significant differences between ranks 1 and 2 on the one hand and ranks 3 to 5 on the other hand, there is a significant distinction between three levels of importance in post-game ranking, mainly caused by an averagely higher ranking of one's own quality's importance (Pillai's trace value (V) = 0.87, F(1, 123) = 11.695, p = .001 < .05*) and a lower ranking of shorter delivery times (V = 0.81, F(1, 123) = 10.848, p = .001 < .05*) after playing the game.

4.7 Requirements for Data quality

The participants also had to rank different requirements regarding their demands on the provision of data. There was no significant difference in the average rankings of any of the factors before and after playing the game ($p > .05$, n.s. for all pre-post factor pairs); therefor, the absolute positions were equal in both pre- and post-game ranking. Participants identified the data quality as the most important aspect ($M = 1.8$, $SD = 0.9$), followed by the visualization of data ($M = 2.3$, $SD = 1.1$), decision support ($M = 2.8$, $SD = 1.2$) and the volume of data, as shown in Table 2. Pairwise comparison revealed that there is no significant difference between the average rankings of "Good data visualization" and "Decision support" ($p = .059$, n.s.). In contrast, for all other comparisons of two factors the criterion of significance ($p < .05$, n.s. for all comparisons) was reached.

5 Discussion

Regarding the technical factors influencing game complexity we learned the easiest condition is the one without drops in either the supplier's quality or the internal production quality. To our surprise, however, we found that the most difficult condition to play is one with drops only in the internal production quality drops, but the supplier's quality stays constant. Counterintuitively, this condition is even more difficult to play than the condition in which both qualities drop. We suspect that to be the case, because the consequences of the quality drops are easier to notice within the company dashboard, as the number of returned parts increases and the incoming quality decreases (two visible changes), while only one measure changes if only the production quality decreases.

Interestingly, the display of traffic lights indicating the supplier's quality and the internal production quality did not influence the decision quality of the players and the performance within the game. Interviews with players after the game suggest that players had difficulties to understand the correct meaning of the traffic signals.

While the investigation of the game mechanics yielded clear findings, the search for human factors that explain performance was only partially successful in this study. We learned underlying factors exist that explain game performance, as players who did well in the first round of the game also did well in the second round (i.e. high correlation of the performances of the first and second round of the game). However none of the variables assessed prior to the interaction with the game explained game performance with adequate accuracy. Surprisingly, the positive impact of high technical self-efficacy on performance [9] could not be replicated within this study. Nonetheless, players with good performance can be differentiated from players with bad performance when in-game metrics or the post-game survey are considered. First, players who achieved higher profits in the game took more time than players who achieved lower profits. Second, good players not only spent more time on the game, they also perform more changes within the game's decision cockpit. Both findings are in line with previous studies [14] and suggest that intense engagement with the subject leads to a better performance. It is unclear however, what causes this effect:

Are people who perform better in the game just more motivated, and therefore spend more time on the game and on changes within the game, or do better players have an increased overview over the company data and are therefore able to adapt more quickly to changing scenarios.

Using games as a vehicle to mediate learning processes is getting more and more popular in various disciplines [15]. Our findings suggest that our game-based approach for teaching fundamentals of quality management also works very well. First, we found that the game is learnable and that the player's performance increases from the first to the second round of the game, showing that the players gained expertise in making complex decisions for the simulated company. Second, the intention of the game is to raise the awareness about quality management and shift the attention towards quality management techniques within the game. After the game the players' relative weighting of quality management was significantly higher than before the game. Hence we can conclude, that the Q-I game is a suitable tool for teaching quality management within vocational trainings, university courses or advanced trainings.

6 Summary, Limitations, and Outlook

Contrary to previous studies, we could not identify human factors that explain game performance. We suspect that the small number of participants per experimental condition, the large noise and huge spread within the data makes the dataset difficult to evaluate. In a follow-up study we will therefore reduce the number of experimental factors and increase the number of participants per condition, assuming that this will yield clearer results. Furthermore, the questions assessing the game strategy from the post-game survey will be rephrased and used in the pre-game survey, as we then hope to be able to predict game performance according to player strategy. In addition, we assume that information processing ability is also influencing performance within the game; hence we will closely investigate the effect of information processing capacity and speed on the outcome of the game in a follow-up study.

The traffic signs were conceptualized to indicate the results from quality audits of the supplying company and of the internal production quality, not as indicators that represent current quality levels. However, many people misinterpreted these indicators and assumed that they show exactly that. A future version of the decision cockpit will therefore clarify this issue and provide both, a clear indicator of the current supplier quality and the current production quality, as well as clear indicators that represent the results from quality audits.

The overall rating of the game was fairly positive and we found that it increased the awareness of the importance of quality management in supply chain management.

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