Human Factors in Supply Chain Management – Decision Making in Complex Logistic Scenarios

Philipp Brauner[1], Simone Runge[2], Marcel Groten[2], Günther Schuh[2,3], and Martina Ziefle[1]

[1] Human-Computer-Interaction Center (HCIC)
[2] Institute for Industrial Management (FIR)
[3] Laboratory of Machine Tools and Production Engineering (WZL)
RWTH Aachen University, Germany
{philipp.brauner,Simone.Runge,Marcel.Groten}@fir.rwth-aachen.de, G.Schuh@wzl.rwth-aachen.de, ziefle@comm.rwth-aachen.de

Abstract. Human behavior in supply chains is insufficiently explored. Wrong decisions by decision makers leads to insufficient behavior and lower performance not only for the decision maker, but also for other stakeholders along the supply chain. In order to study the complex decision situation, we developed a supply chain game in which we studied experimentally the decisions of different stakeholder within the chain. 121 participants took part in a web-based supply chain game. We investigated the effects of gender, personality and technical competency on the performance within the supply chain. Also, learnability and the effect of presence of point-of-sale data are investigated. Performance depended on the position within the chain and fluctuating stock levels were observed in form of the bullwhip effect. Furthermore, we found that risk taking had an impact on the performance and that the performance improved after the first round of the game.

Keywords: Supply Chain Management, User Diversity, Gamer types, Human Behavior, Beer Game, Serious Gaming.

1 Motivation and Related work

If your local supermarket spontaneously offers groceries at a discount, you might be happy about the bargain. Supply chain managers, however, might worry about the consequences a discount has on the downstream supply chain. One crucial consequence is the so-called "*bullwhip effect*": The bullwhip effect is a phenomenon in which a relatively small variation in the orders of a customer at one end of a supply chain causes escalating fluctuations in the stock levels and orders along a supply chain. Increasing demand at the n^{th} tier in a supply chain is usually over-compensated by an even grater increase of the demand at the $n+1^{th}$ tier of the chain. As a result, the curve mapping the stock levels along the time looks similar to a whiplash, hence the name "*bullwhip effect*". It has been first described by Forrester in the 1960s [5] and

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replicated in a series of studies and was found in real world companies, such as Procter & Gamble or Hewlett Packard [6, 7].

Typical symptoms caused by the bullwhip effect are the following: First, excessive inventory and safety stocks, which – while lowering the amplitude of the bullwhip effect – cause additional costs for storing goods. Second, production forecasts are poor, resulting in unsatisfactory production planning. Third, production capacities are insufficiently utilized. Finally, service rates descent, meaning that requested products are not delivered in time.

According to Lee et al. [6] key reasons of the bullwhip effect are the existence of lead times of information and material in a supply chain. A member of the supply chain will not be able to follow a change of the final demand directly, because of the following three reasons: First, s/he will not receive the information immediately, as information is not delivered in real time. Second, safety stocks along the supply chain also delay the information flow. Third, supply chain members are not able to adapt their capacity, demands and deliveries immediately.

Other factors causing or magnifying the bullwhip effect are *demand forecast updating*, *order batching, price fluctuations* and *rationing and shortage gaming* [6]. *Order batching* refers to the strategy of companies to order sub-components at fixed rhythms or fixed quantities and not directly when an order comes in. Hence, an additional delay or further fluctuations occur. The *demand forecast* is predicted by each supplier along a supply chain individually. This is based on the data and experience of the past, received information from its customers, individual estimation of e.g. the economic situation and an internal safety stock. Mistakes in these individual forecast planning transmit upwards and can cause a higher variability. This variability will even further increase, if the lead times of the resupply along the supply chain grow. *Price fluctuations* also contribute to the bullwhip effect, as outlined in the beginning of this paper. When components are offered in a special promotion, customers may be inclined to order larger quantities. Also, the price level is usually linked to the order size. Therefore, often more components than needed are procured. *Rationing and shortage gaming* also increase security stocks and the bullwhip effect. If the capacity of a supplier is lower than the current demand, only a share of a given order will be delivered. Therefore, orders are typically increased to counterbalance this reduction. Though, if the orders can be fulfilled by the supplier, e.g. because the capacities have been increased, this gaming behavior causes again increasing stocks and a magnified bullwhip effect.

Possible counter-measures against the fluctuations along the supply chain are presented in [6]. They include the sharing of point-of-sale data, inventory data and capacities and therefore simplifying the demand forecast, faster ordering systems and the reduction of lead times, as well as Everyday Low Prices to reduce variations induced by special promotional offers. Another approach to reduce the bullwhip effect is the implementation of High Resolution Supply Chain Management (HRSCM) [9]. HRSCM aims on high information transparency between the stakeholders in a supply chain in combination with decentralized, independently acting and self-optimizing control loops. While many shortcomings of traditional supply chains are bettered. Still, this approach focuses solely on technical optimizations of supply chains and not

on humans in the loop, who also usually take a great part in forecasting the demand and deciding what quantities to order from which supplier.
The bullwhip effect is described well in literature and many counter-measures from the side of industrial management are proposed to avoid or reduce the bullwhip effect (see [6]). Still, the underlying human factors are not yet sufficiently explored.

The beer distribution game was originally developed at the MIT in the 1960 [7]. It is used to simulate a dynamic build-to-stock (in contrast to build-to-order) supply chain. The chain consists of four tiers and is used to explain the approach of system dynamics and the bullwhip effect.

Nienhaus, Ziegenbein und Duijts investigated the human influence on the Bullwhip effect [7]. They compared models of supply chains that were purely based on independently acting computer agents with supply chains with humans as co-players. A central finding of the study was that both supply chains differed. Hence, humans and computer agent acted differently and human factors have to be considered as a factor influencing supply chains. Furthermore, they did a post-hoc classification of human strategies in a "panic" and a "safe harbor" strategy. In their study some humans played a "safe harbor" strategy, which means that they always tried to maintain a specific stock level, whereas others tried to keep the stock level as low as possible, resulting in panic reactions as soon as the customer demand rises ("*panic strategy*").

2 Method

In order to understand how human factors influence the individual stakeholder performance as well as the overall performance in a supply chain, we pursued an experimental approach, in which participants acted as different stakeholders within the supply chain. Before interacting with the supply chain we measured several personality factors and related them to the outcome of the game. In the following the model of the supply chain, the experimental variables and the sample is detailed.

2.1 Model of the Beer Game

We implemented a web-based version of the Beer Game, that allows users to participate in a supply chain and to experience the difficulties to balance stock levels while incoming orders and deliveries are subject to variations.

The game reassembles a supply chain for one specific good (e.g. in this case for beer crates). The supply chain consists of the four positions *retailer*, *wholesaler*, *distributor* and *factory* (see Fig.1for a schematic overview). Each position has number of this good in its stock. If the predecessor in the supply chain (e.g. the predecessor of the distributor is the wholesaler) is ordering goods, the number of goods is removed from the stock and transferred to the predecessor. To replenish the stock, the position orders a number of goods from its successor (e.g. the distributor orders from the factory). A computer-simulated customer that orders goods from the retailer triggers the supply chain.

As in the original Beer Game (and in real-world supply chains) the difficulty arises from the time delay between submission of an order and its fulfillment. It takes one week until a submitted order reaches the successor in the supply chain and additional two weeks until the goods arrive at the ordering position. Notable exception is the customer: His/her order is instantly available to the retailer and she/he also instantly receives the purchased goods.

Even if a player's stock level is lower than the request, the request is still fulfilled. However, the stock will then get negative and penalties have to be paid (*1.00$* per good). Also, each position has to pay stock keeping costs for surplus of goods in stock (*0,50$* per good). Therefore, each player has to minimize the stock level while at the same time ensuring that orders can be fulfilled.

The computer-simulated customer acts according to a fixed order function: At the beginning of the game the customer is ordering 4 goods in each of the first 5 rounds. After that, the order increases to 8 goods per round for the rest of the game.

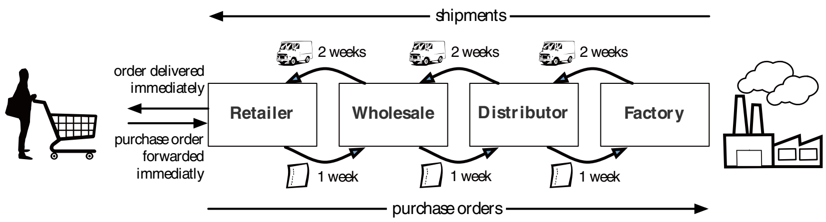

Fig. 1. Schematic diagram of the supply chain

2.2 Independent Variables

A series of demographical and psychometrics were assessed before the experiment. All ratings were measured with 4-level Likert scales.

Demographics and personality factors: As independent variables gender, age and highest formal educational attainment were collected.

Expertise: The study was targeted at novices that have no or limited experience in the logistics domain. To check this precondition, the subjects had to subjectively rate their experience in logistics and related domains, such as economics.

Technical Self-Efficacy (TSE) [2]*:* This scale has shown to be valuable in understanding performance and learning in many computer mediated environments [1, 3].

Personality type: To analyze the effect of personality traits on the performance we used the Five Factor Model (FFM)[4]. This model describes the human personality by five dimensions: Openness (openness to new experiences vs. cautiousness), conscientiousness (self-discipline vs. easy-going), extraversion (sociability vs. solitariness), agreeableness (friendliness vs. unkindness) and neuroticism (self-confident vs. sensitive). Also, the subscale "need for security" was used. These factors were measured with a German version of the Big Five inventory[8]. For test-economy the number of items was reduced from ten to three by a factor analysis.

Player types: Furthermore, we measured the motives for playing board or computer games with questions such as "*I like to understand the underlying strategy of a* *game*" or "*I like to play games because it is popular among my friends*". This scale is based on Yee's study of player types found in online games [10] and categorizes gamers along the three main dimensions *Social*, *Achievement* and *Immersion*. People who like to socialize, either within or outside the game, rank high on the *Social* scale. Players who are driven by understanding the game mechanics or like collecting material and money rank high on the *Achievement* scale. If diving into roles or customizing their characters drives people they get high values on the *Immersion* scale.

2.3 Experimental Variables

The position within the supply chain was varied as a between-subjects variable (e.g. the position in the supply chain was chosen randomly, still it was the same for both rounds of the game). To control interactions across individuals we substituted the other players by computer players with a fixed strategy. Previous studies showed that the availability of point-of-sale data lowers the bullwhip effect. In this study we varied the availability of this data as a within-subject variable: Participants played both with and without point-of-sale data and the order of both conditions was randomized.

2.4 Dependent Variables

Performance within the supply chain. Behavior and performance within the game was measured through interaction logs of the web application. We looked at costs and stock levels of each position in each round and the total costs of the supply chain.

2.5 Experimental Setup

The participants were asked by email, social networks and personally to visit our beer game website. There, a survey assessed the demographics and personality factors as described above. Then, two rounds of the beer game were played. 173 people started the only survey, 128 have completed both rounds of the game and 126 people finished the post-survey. We revised the dataset and eliminated 5 cases with duplicated data or without meaningful gameplay (e.g. greatly exaggerated orders). The final dataset contains the gameplay and the questionnaire data from 121 people. The game was played for 25 rounds and as the players could optimize his/her strategy towards the end. Hence, only data from week 1 to 20 will be presented.

2.6 Participants

Of the 121 participants 61 (51%) were male and 57 female (48%). The age mean is 27.1 years (±6.1 years). The youngest participant is 19 years old and the oldest participants 54 years. The majority (68%) reported having no substantial prior knowledge in the areas of logistics, supply chain management, economy or business administration. 32% reported at least some knowledge either of these domains.

Gender has an significant effect on the participant's subjective technical competency (TSE), with women having a lower TSE ($M_{♀}$=3.15, ±.58) than men ($M_{♂}$=3.53, ±.45) (F(1,117)=14,363, p=.000<.05). This finding is in line with prior research [3]. Regarding the five factor model, our sample is also consistent with common findings: Men are less extraverted than women and show lower levels of neuroticism (see Table 1). Significant gender differences were found regarding the *Achievement* Scale in Yee's player types with men being more attracted to achievement ($M_{♂}$=2.84, ±.48) than women ($M_{♀}$=2.53, ±.54) (F(1,108)=10.014, p=.002 < .05). No differences were found on the *Social* (M_{avg}=2.55, ±.42) and *Immersion* dimension (M_{avg}=2.67, ±.65).

Table 1. Gender differences regarding the Five Factor Model ((* significant at p<.05, $^{(*)}$ at p<.1))

	Openness	Conscien-tiousness	Extraversion	Agreeableness	Neuroticism	Need for Security
Men	3.30	2.89	3.01	3.29	1.96	3.02
Women	3.29	3.10	3.27	3.43	2.23	3.13
F(1,108)	.003	3.413	4.287	1.283	3.601	.871
p	.957	.067$^{(*)}$	.041*	.260	.060$^{(*)}$	.353

3 Results

The data was analyzed using bivariate correlations, χ^2-tests, uni- and multivariate analyses of variance (ANOVA/MANOVA) with a significance level of α=*.05*. Pillai values were used for the significance of the omnibus F-tests in the MANOVAs.

3.1 Bullwhip Effect

The Bullwhip effect is clearly observable (see Fig. 2). After the 5th week the customer increases his order from 4 to 8 good/week. This immediately affects the retailer's orders that increase from 5.1 to 7.5. Each week this increase is observable at the next position in the supply chain and eventually reaches the factory in week 9.

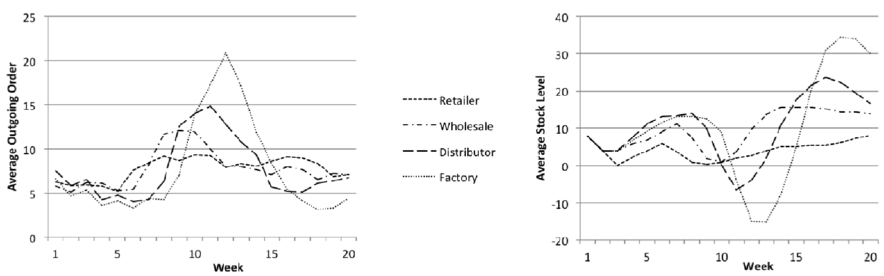

Fig. 2. Average stock level (left) and average outgoing orders (right) by week and position

3.2 Effect of Position in the Supply Chain

As expected the position within the supply chain had a significant effect on the total cost of a player and the average costs increase along the supply chain: Retailers accumulated less costs (C_R=87,95, ±46.5) than wholesalers (C_W=156,14, ±124.0), distributors (C_D=158,76, ±84.4) and factory players (C_F=223,76, ±101.6) (see Fig. 3, left). This effect is significant (F(3,108)=9,807, p<.001). A post-hoc Tukey-HSD test revealed that the mean scores from the retailer differ significantly from all other positions. Factory and distributor scores differ significantly. However, factory and wholesaler score closely miss the significance level with *p=.052>.05*. The mean scores of the wholesaler and the distributor do not differ significantly. Likewise the average spread ($max(stock_{Week\ j}) - min(stock_{Week\ i})$) differed significantly along the supply chain (F(3,108)=13.105, p<.001). A post-hoc test revealed that the spread differed significantly for all positions but wholesaler and distributor (see Fig 3, right).

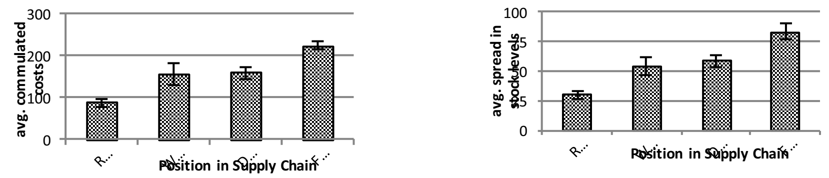

Fig. 3. Average costs (left) and average stock level spread along the supply chain (right)

3.3 Effect of Point-of-Sale Data

Contrary to numerous previous studies, the presence of point-of-sale (POS) data did not lower the costs in the supply chain. In the first round players without POS data actually produced slightly lower costs ($C_{noPOS}=198$, ± 144) than player with POS data ($C_{POS}=221$, ± 154). Yet, both differences are not significant, when the position is statistically controlled (F(1,104)=2.368, p=.075>.05, n.s.; F(3,104)=1.993, p=.120>.05, n.s.). However, we found that the POS data reduced the fluctuations of the supply chain: It was easier for players with POS data to maintain positive stock levels and avoid peaks (e.g. in week 14 the average stock level for factory players without POS was -14.1, while factory players with POS data had stock levels of -1.6 (see Fig 4). Still, the reduced variations did not reduce the final costs generated in the game.

Fig. 4. Effect of Point-Of-Sale data on avg. stock levels of for distributor (l.) and factory (r.)

3.4 Effect of Repetition

There is a strong significant correlation between player's cost in the 1st and the 2nd round of the game (r=*.628*, *p=.000<.05**). With the position in the supply chain controlled the partial correlation between the costs in the 1st and 2nd round is also strong and significant (*r=.560, p=.000<.05**). Hence, factors must exist than explain good or bad performance in the supply chain, otherwise, if no such factors would exist, the costs of the 1st and 2nd round would be uncorrelated. Furthermore, the player's average cost decreases significantly between the first (C_{1st}=160, ±64) and the 2nd round of the game (C_{2nd}=143, ±47) when the position within the supply chain is controlled (F(1,111)=4.204, p=.043<.05*).

3.5 Effects of User Diversity

Effects of gender: Women generated more costs than men ($C_{♀}$=621, ±276, $C_{♂}$513, ±122). Although women's cost were higher on all four positions of the chain, this effect is not significant (F(1,102)=4.732, p=.110, n.s.). We suspected that the large standard deviation prevents significant results, thus we used a different metric for analyzing the performance: The stock level spread ($max(stock_{Week\,j}) - min(stock_{Week\,i})$). In contrast to players with a low spread, players with a large spread have difficulties to maintain a constant stock level. They are not only victims of the bullwhip effect, but also amplify it, as variations in the stock level usually cause wriggly outgoing orders. Indeed, gender actually influences the spread (F(1, 102)=8.897, p=.065<.1) and men have a lower stock level spread (S_m=35, ±29) than women (S_w=39, ±28).

Effect of technical self efficacy: Technical self-efficacy (TSE) influenced the performance and players with low TSE performed worse (C_{low}=167, ±141) than players with high TSE (C_{high}=124, ±101) (F(1,109)=4,018, p=.048<.05). The same result was found for the spread in stock levels.

Effects of need for security: The "need for security" subscale of the personality inventory shows significant differences (F(1,103)=4.872, p=.030<.05) with players having a high need for security having a higher spread (S_{high}=45, ±29) than players with a low need for security (S_{low}=33, ±37). Again, this difference fades if total costs are considered (F(1,103)=2.623, p=.108, n.s.) (C_{low}=128, ±113; C_{high}=173, ±135).

3.6 Effect of Gamer Type

Analyzing the effect of the gamer type on the game performance. Contradicting expectations, the *Desire for achievement* did not impact the performance (F(2,101)=.060, V=.001, p=.942, n.s.). However, desire for *Social* interaction (F(2,101)=5.489, V=.098, p=.005 < .05) and *Immersion* (F(2,101)=3.203, V=.060, p=.045<.05) influences the performance. Participants with high interest in social interactions performed significantly better (C_{soc}=131, ±76) people with low interest in social interaction (M_{asoc}=177, ±120). Likewise, high immersion players performed better ($M_{imm,high}$=137, ±67) than low immersion player ($M_{imm,low}$=165, ±120).

4 Discussion

The experimental approach used to study the complexly linked factors and to uncover human factors involved in supply chains revealed to be very useful. The supply chain was hit by the bullwhip effect and the effect increases with the distance from customer to player. Players performed equally well respective bad in the 1st and the 2nd round of the game. Hence, underlying factors must exist that explain player's performance. The data gives an insight in these factors, however they are not yet fully understood.

Social behavior increases performance, while focussing on his/her own interests is punished by the market. Also, immersing in the task of managing a supply chain was rewarded by low costs. The player's personality, modeled by the Five Factors Model did not impact performance within the supply chains, showing a high universality of the findings. Gender and technical self-efficacy influenced performance, with women and persons with lower self-efficacy performing worse. As gender and technical self-efficacy are connected [3], the lower performance of women can be referred to their lower self-efficacy levels. Corroborating previous findings in other contexts, we see once more the strong power of technical self-efficacy as a cognitive control mechanism that immensely controls human behavior [1].

The expected finding of a softening effect of point-of-sale data on the turbulences in supply chains could not be replicated as players performed equally well with and without the presence of this data. This can be referred to two major sources: First, our participants were novices with no prior knowledge about the game or supply chain management. Getting familiar with the complexity of the supply chain over the experimental phase may have veiled effects. Future studies will clarify effects with experts having higher domain knowledge. Second, as only a comparatively small sample size was given here, the non-linear nature of the costs and stock levels and the strong influence of the position on the performance, make the current dataset vulnerable regarding statistical rigidity. Hence, further studies have to be carried out in which more linear metrics are utilized or only one or two positions are considered, increasing the sample size for the remaining position.

To rule our effects by interactions with other human players, we modeled the co-players by artificial agents in this study. We noticed though that our agents performed very well and that the supply chains showed less turbulence than usual. Further studies will investigate the interaction of human players and different personality traits.

5 Summary, Limitations and Outlook

We presented a first glimpse on human behavior in supply chains. Still our research is just at the beginning with many influential factors not varied as an experimental condition or even discovered. We used a linear supply chain with four different positions. Reality is though more complex and more interactions between stakeholders occur that have to be investigated. Furthermore, the co-players were modeled by computer agents and it is unclear if our results are transferable to games, where all positions are played by humans and what interactions might occur when different personality types cooperate in a supply chain. Consequently, further research must evolve in four directions: First, identify and investigate additional factors that influence decision making along the model of a linear supply chain. Possible factors include, but are not limited to, the spread between penalty payments and stock keeping costs, variations in delivery reliability in regard to time or quantity and variations in the order function of the customer. Second, develop and evaluate an ecologically valid supply chain network, which extends to both additional positions horizontally as well as vertically. Decision conflicts, such as choosing the right supplier, have not been investigated in a model like this before. Third, evaluate how results from the "clean" experimental conditions can be transferred to either more realistic scenarios with multiple human players or how the results perform in real life to ensure external validity. Finally, investigate if this game is a suitable educational tool to train future managers and to evaluate if these trainings strengthen the competitiveness of companies.

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