Combining Behavioral Experiments and Agent-based Social Simulation to Support Trust-aware Decision-making in Supply Chains

Diego de Siqueira Braga[1], Marco Niemann[1], Bernd Hellingrath[1] and Fernando Buarque de L. Neto[2]
[1] *Westfälische Wilhelms-Universität Münster, Münster, Germany*
[2] *University of Pernambuco, Recife, Pernambuco, Brazil*

Keywords: Social Simulation, Trust, Bullwhip Effect, ABSS, Behavioral Experiment, Behavior Modeling.

Abstract: Trust is seen as one of the most important dimensions in developing and maintaining fruitful business relationships and has deep impact on the decision-making process in the supply chain planning. Despite its importance, very limited research has been done in the trust-aware decision-making field. This paper aims to experimentally examine how trust can be assessed over different dimensions and then be used to support decision-making in order to reduce the Bullwhip Effect, which is one of the biggest efficiency problems shown by supply chains of highly interconnected organizations. As industry is generally reluctant to provide data due to privacy concerns and trade secret protection, the authors of this paper, designed and conducted a web-based trust behavioral experiment. The data collected was used to evaluate the proposed trust mechanism through an Agent-Based Social Simulation. The results revealed that it is possible to infer trust relationships from behavioral experiments and historical based data, and use these relationships to influence the procurement, ordering and information sharing process. Although additional research is still necessary, the preliminary results revealed that the use of computational trust mechanisms can be helpful to lower the Bullwhip Effect.

1 INTRODUCTION

The issues of trust have been an active research area in different disciplines including economics (Greif et al., 1994), sociology (Bachmann, 2001), business information systems (Ba and Pavlou, 2002; Ba et al., 2003; Resnick and Zeckhauser, 2002), information security (Weeks, 2001), online auctions (Houser and Wooders, 2006), social relationships (Castelfranchi and Falcone, 1998), multi-agent systems (Braynov and Sandholm, 2002b; Braynov and Sandholm, 2002a; Yu and Singh, 2002; Zacharia et al., 2000), and supply chains (Laeequddin et al., 2010).

Researchers so far did not agree on a commonly accepted definition of trust. Instead there is only some elements - like the Trustor (*trusting party*) and Trustee (*trusted party*) concept - that most authors can agree on. Furthermore trust can be seen the trade-off between potential risk and expected gain (Rousseau et al., 1998). In this context, trust is the result of prior (positive) experiences from mutual interactions with other parties (Ring and Van de Ven, 1994; Kim, 2009). As an effect of this dependency trust is a dynamic property, readjusting itself based on new interaction outcomes (Abdul-Rahman and Hailes, 2000).

1.1 Trust in Supply Chains

A Supply Chain (SC) is a system of semi-autonomous business entities (i.e. suppliers, manufacturer, retailers, customers), linked by material, financial and information flows across several processes and activities (Christopher, 1999). Such modern SC are typically viewed as socio-technical systems (linking society's social and organizations' technical aspects) (De Bruijn and Herder, 2009).

Organizations in a SC face a vast number of problems, such as decision making (i.e. inventory management), where interdependent decisions are commonly managed separately. Additionally organizations are not isolated, but influence each other (Chaib-draa and Müller, 2006). One of the biggest SC efficiency problems, the so called Bullwhip Effect (BWE), describes the phenomenon of increasing upstream order variances (Forrester, 1958). Prediction and planning are aggravated by high levels of order variances, decreasing customer service levels and lowering SC's competitiveness. Common coping strategies include increased stock levels and information sharing. While the first increases costs even further, the second one is considered a non-simple

de Siqueira Braga D., Niemann M., Hellingrath B. and de L. Neto F.
Combining Behavioral Experiments and Agent-based Social Simulation to Support Trust-aware Decision-making in Supply Chains.
DOI: 10.5220/0006200802600267
In *Proceedings of the 9th International Conference on Agents and Artificial Intelligence (ICAART 2017)*, pages 260-267
ISBN: 978-989-758-219-6

task. Information sharing can be influenced by formal (e.g. contracts) or informal (e.g. trust) interactions. So SC performance analysis and improvement requires consideration of both aspects and their interdependencies (Ottens et al., 2006). Since the SC domain is very dynamic, trust is considered an essential tool to develop and manage business relationships, by lowering transaction costs and shifting to continuous exchange relationships (Kwon and Suh, 2005; Raimondo, 2000; Tykhonov et al., 2008). These effects, predicted by theory, have been validated by empirical analysis (Özer et al., 2011) and real-world environment studies (Ha et al., 2011).

1.2 Computational Trust

Trust was first introduced as a measurable property of an entity in computer science by (Marsh, 1994). Since then computational trust has grown into a broad research area, comprising lots of different trust and reputation models (Sabater and Sierra, 2005; Yu et al., 2013).

Despite its importance, the conducted SC trust research mostly focuses on its use for partner selection, while explicit inclusion into the decision making process would be desirable to facilitate information and asset sharing (Burnett et al., 2014).

Performance evaluation is typically either conducted via real world datasets (scarce due to privacy issues) or the more widely used simulation-based evaluation (Yu et al., 2013).

2 TRUST BEHAVIORAL EXPERIMENT

Triggered by the lack of trust related data and motivated by the growing interest in behavioral research in supply chain management (Donohue and Siemsen, 2011) a trust experiment is proposed. It is expected that the experiment will gather information regarding individuals' behavior during procurement, and ordering decisions considering trust relations in the context of supply chains.

The experiment aims at (i) exposing different relevance profiles; (ii) evaluating order assessment concerning trust dimensions; and (iii) validation of additional features of the trust mechanism (see Section 3).

The participant acts as a retailer aiming to fulfill the demand of a customer by ordering from a various number of suppliers. Each supplier has a different profile (explained in Section 2). In addition, the participant has to consider inventory and back order costs as well as decreasing payments by the customer for each round not delivering.

Gamification concepts such as a high score list and progress bars were used in order to increase the participants motivation.

The experiment consists of three parts. The first part aims at exposing the relevance profiles regarding the procurement and trust agents. The goal of the second part is to expose the trust assessment. The last part consists of a questionnaire to evaluate the decisions made by the participants.

Firstly, the suppliers have different profiles based on a price per product, an expected delivery time and a trust value to evaluate the procurement decisions. After nearly 20 rounds the experiment form is modified in order to capture information regarding the preferences of the participants regarding the four dimensions: $\{$*Reliability, Quality, Competence, Shared Values*$\}$.

The goal of the second part is to expose the trust assessment. Therefore, the participant has to assess each dimension regarding the received order. Each order has a specific delay or failure rate regarding the delivered products. Concerning these factors, the participant has to adjust the existing rating of each dimension by a number between 0 and 100. Thereby, it is possible to analyze individuals' behavior regarding the assessment of each dimension – for example, how the participant deals with an order delay of one week.

The third part is a questionnaire aiming to assess the participants decisions. Firstly, the relevance profiles are recalled so that each participant has to evaluate his/her behavior regarding price, delivery time and trust or the four trust dimensions. Afterwards, the participant demonstrates his/her preferences regarding indirect and direct trust by rating the utilization of trust-relating information given by others. Finally, the experiment evaluates which level of trustworthiness is necessary for each participant to share information with suppliers.

Results and Analysis

After comparing the relevance profiles given by the participants with their real ordering decisions three main segments regarding the procurement process were identified. The biggest one (group A) having a share of round 26% of the whole participants is mainly focusing on a relatively low price and a short delivery time. A trust value is not that important for this group. To the second group (group B) the price is the most important value for decision-making where to order without focusing very much on a delivery time or the trust value. About 23% of all participants

Table 1: Procurement profiles.

Group	Price	Delivery Time	Trust
A	44%	41,5%	14,5%
B	63%	22,5%	14,5%
C	34%	34%	32%

Table 2: Relevance of Trust and Indirect Trust.

Group	Direct	Indirect
A	65%	35%
B	73,75%	26,25%
C	58%	42%

used this kind of relevance profile for choosing their suppliers. The last big group (group C) is a balanced one. It has a share of 17% and focuses on price, delivery time and trust almost equally. The profiles with their rounded relevance values can be seen in Table 1.

In Table 1 the different profiles of group A, B and C can be seen regarding the procurement decision-making. Each value represents the importance of each dimension in the calculation during the decision-making process.

After exposing the trust relevance profiles, these three groups were analyzed regarding their decisions made in the second part of the experiment. In Table 3 it is possible to see that *Reliability* and *Quality* were the most important dimensions. Having equal number in groups A and C, and small differences when considering the ratings for the other two dimensions. In group B the observed value for the *Reliability* dimension was higher in comparison with groups A and C (i.e. 45,5%), which is interesting as it contradicts some results of Table 1. There Group B valuate price almost three times more important as delivery time. But when assessing the trust profile where price is out of scope, *Reliability* measured by the on-time KPI (see Section 3) is the most important trust property to this group.

Furthermore, the analysis exposed how these groups consider indirect trust values given by other actors to decide which supplier to choose comparing to their own direct value. The different importance profiles regarding this weighting of direct or indirect trust can be seen in Table 2.

It was also assessed the necessary trustworthiness a supplier must have so that participants share information. Table 4 shows the identified trust threshold values for information sharing to happen. The first level of information sharing is supposed to tell a supplier if one will order from him in the next round. The second level is about sharing the order amount one round earlier with the supplier.

Another important part of the experiment was to identify how participants assess different orders. The experiment exposed that participants assess, in average, a delay of one week by decreasing the reliability value by round 8,21 % and increase it by round 4,89 % for each order without a delay. The *Quality* dimension is assessed based on the percentage of failure rate so that participants decrease it by round 0,72 % for each percentage of failure (e.g. decrease of quality dimension by 7,2% when having a failure rate of 10% related to a specific order). For each received order without any defective products the *Quality* value is increased by round 4,76 %. For every received order which is perceived as bad by the participants the *Competence* value is decreased by 3,7%, and increased by 0,5% for every order perceived as good (these values can be seen in Table 5). Considering the results present in Table 5 one can see that received orders which are perceived as negative are assessed more strictly regarding each dimension. Because of this higher impact in the dimension, a bad order can not be equalized by a proportionally good order. This observation reinforces the findings regarding the difficulties of mitigating damaged trust relationships already present in literature (Kim et al., 2006).

Table 3: Trust profiles. Legend: Competence (C), Reliability (R), Quality (Q), Shared Values (SV).

Group	C	R	Q	SV
A	22%	31%	31%	16%
B	10%	45,5%	30,5%	14%
C	25%	31%	31%	13%

Table 4: Trust threshold values for information sharing.

Group	Share order intention	Share demand
A	53%	67%
B	45%	71,25%
C	58,5%	62,5%

3 SOCIAL SUPPLY CHAIN SIMULATION

The simulation allowed an examination of trust assessments through different dimensions and the use of trust in lowering the BWE.

The supply chain conceptualized for the simulation experiment has been constructed with six different, commonly used actors: suppliers, manufacturers, distributors, wholesalers, retailers and customers (Mentzer et al., 2001; La Londe and Masters, 1994). In this model the *supplier* is considered to be a source of raw materials for the *manufacturer*. For the sake of simplicity it is assumed that the *supplier* is always

Table 5: Participants Trust Assessment.

Assessment	Reliability	Quality	Competence
Perceived as bad	-8,21 % per week	-0,72% per percentage of failure	-3,7%
Perceived as good	+4,89 % per week	+4,76%	+0,5%

able to provide ordered goods. After refinement by the *manufacturer* the products are delivered to the *wholesalers* via the *distributors*. The *wholesalers* act as the supplying entities for the *retailers* who sell the product to the customer. Beside this unidirectional flow of material the proposed supply chain model allows a bidirectional flow of information.

In addition to the six common actors, this paper introduces another entity: The *lying actor*. It conceptually differs from the previous constructs, as it does not aim at modeling a new type of SC member, but rather represents one of the other types with the addition of lying in form of opportunistic behavior. Typical behavior exhibited by such an actor would be ordering new goods at two suppliers to counter potential shipment delays. On receipt of the earliest delivery it would automatically cancel all other orders. Doing so these agents will increase the BWE and thus can serve as disturbing factors in a SC that are to be ruled out via trust-based decision-making.

Agents

A set of nine different agents was conceptualized to model the behavior of the different SC participants. A majority of them aims at the fulfillment of typical SC tasks. For example the *inventory agent* is responsible for managing both the incoming as well as outgoing product stocks of an actor. It makes use of the perpetual as well as the order-up-to level policy (Dejonckheere et al., 2003; Clark and Scarf, 1960).

Additionally a *forecast agent* is implemented based on the OpenForecast library (Gould, 2011), allowing an actor to predict the demand of the next period.

A *procurement agent* is added as a supplier selection entity. It aggregates trust information from both *trust agent* as well as *indirect trust agent* (these concepts are going to be introduced later in this Section) and combines it with price and delivery time information obtained from the *delivery agent*. Based on three weighting parameters (one per criterion) the agent selects the best supplier for the follow up transaction. If the parent actor is a *lying actor* the *delivery agent* additionally selects the second best supplier as well.

The actual ordering of goods is handled by the *order agent*. It combines the forecast, a potential backlog as well as inventory orders into one final order amount. For the order fulfillment the *order agent* uses the best supplier suggested by the *procurement agent*. If the parent actor is a *lying actor*, the same order will be placed with the second best supplier. Whenever the agent receives goods they are checked for completeness and integrity to sort out defect ones.

In order to handle the downstream flow of material of an actor, the *delivery agent* has been introduced. It receives the orders of the downstream partner and is responsible for their shipment. Whenever a full delivery is not possible, the available parts are shipped while the remaining items are added to the agents backlog. A secondary function of the agent is the delivery of historical transaction data for the *forecast agent*.

Logically in-between the *order agent* and the *delivery agent* the *production agent* is settled. They are transforming incoming goods into a new product. The exact design of this transformation is specified by so-called production policies. For each supply chain actor such a policy specifies the used input, production time and a specific failure rate.

While the prior six agents carry out core SC tasks, the following two deal with trust related computations needed for trust-aware decision-making. The first, the *trust agent*, aims at the evaluation of the direct trust score. Direct in this domain implies that only the agent's own set of information is used. Despite, as (Pinyol and Sabater-Mir, 2013; Sabater and Sierra, 2005) observe, most models still only consider a single trust dimension, it was deemed beneficial to use a multi-dimensional model instead. This supports the paper's goal to enable a better understanding of trust to use it for trust-aware decision-making. A direct implication is that analyzing trust in a less aggregated fashion is desirable. Consequently, trust assessment is conducted considering the quadruple {*Reliability, Quality, Competence, Shared Values*} (Haghpanah and DesJardins, 2010; Lin et al., 2005; Handfield, 2003; Morgan and Hunt, 1994). *Reliability* is assessed based on the *On-Time KPI* (ServiceNow, 2016), which represents the share of ordered goods arriving on time. Similarly, *Quality* is measured based on the *Undamaged Goods KPI* (ServiceNow, 2016), marking the percentage of undamaged goods after inspection. In order to evaluate the *Competence* of a supplier, the trust agent assesses the order history. Beside the prior three factors only being based on the perceptions of a single agent, *Shared Value* is added to integrate agent similarity into the model. This measure allows to evaluate the degree of equality between two agents ($j \in \{1,2\}$) in their weightings w_{ij} of the quadruple {*Reliability, Quality, Competence, Shared Values*} (Morgan and Hunt, 1994). It is assessed via the euclidean distance between the quadruples of both agents.

The computed value henceforth will be considered as the $OrderFulfillment$ (OF). In combination with the trust dimension weightings of the parent user this value allows to update the trust score assigned to a specific supplier. As a first step the weighted average (again weighted with w) of the difference between $OrderFulfillment$ and weightings w will be computed to obtain a trust update value.

To compute the new trust value the weighted average from above is weighted by and added to the old trust value.

The influence of the impact of the update value can be regulated by a learning rate α. Assigning a low α value will smooth the shift, high values will speed it up.

Additionally an *indirect trust agent* is proposed to account for trust computation from witness information as a second traditional source of trust information (Sabater and Sierra, 2005). It collects all direct trust values other agents assign to suppliers. From there the agent is able to compute a mean trust value for a specific supplier. The degree to which this value will be considered depends on the preferences of the parent actor.

Depending on the degree of trust assigned to a supplier by the evaluating trust agents the actor might share additional information or even assign an open order earlier (referred to as *information sharing* from now).

4 VERIFICATION & VALIDATION

In order to verify the correctness of the implemented agents and actors the commonly used JUnit unit testing framework was used. It appeared to be the most reasonable choice as it was already integrated in the Repast framework (Argonne National Laboratory, 2015).

A special focus of the tests have been the classes used for trust assessment. This way it should be ensured that each dimension was computed correctly to guarantee correct supplier selection.

Apart from these static tests the simulation results have been verified based on already existing prior studies by (Dejonckheere et al., 2004), (Chatfield et al., 2004) and (Chatfield and Pritchard, 2013). The used measure of comparison is the BWE modeled by the total variance amplification (TV_{Amp}), which compares an upstream node's ($k > 0$) order variance with the demand variance of a customer node ($k = 0$) (Chatfield and Pritchard, 2013).

To achieve comparable values the proposed model has been slightly adjusted: First, the SC was restricted to have one actor per tier, neglecting lying actors. Production has been simplified to consider only one input and one output. Apart from production time, no additional temporal effort is considered. The customer demand is normally distributed with $\mathcal{N}(10,1)$.

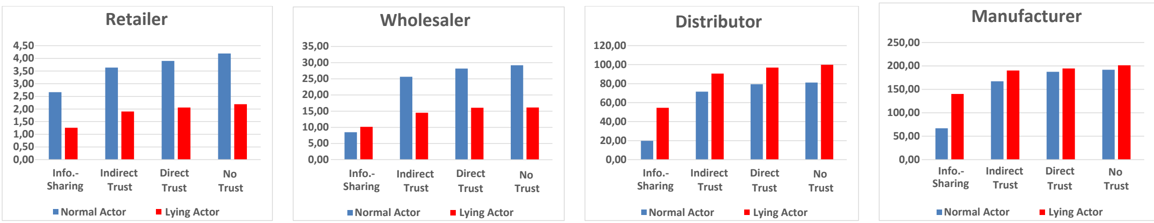
Both models - with and without information sharing - can be assumed to be verified, since the results match those of prior studies as expected. Looking at the results in Tables 6 and 7 values are roughly the same. Especially with regard to the outcomes of (Dejonckheere et al., 2004) the differences are considerably small. The larger gaps with regard to the results of (Chatfield et al., 2004) and (Chatfield and Pritchard, 2013) may be partly based on their use of a custom simulation system called SISCO.

Given this verification, as a next step the effect of the single components (e.g. *trust agent* or *information sharing*) have to be evaluated, to understand their influence on the BWE. The used metric was again TV_{Amp}.

The data acquired through the Trust Behavioral Experiment was used to initialize the different agents in the simulation model. This includes the discovered profiles as well as the identified information sharing threshold values.

Looking at the results presented in Table 8 and Figure 1 several interesting observations can be made. Number one is the fact that for all actors except the *Retailer* the $TVAmp$ value is smallest when all trust and information sharing components are active, but no *Lying Actors* are present. *Retailers* require the presence of *Lying Actors* to that point. On the contrary the worst values come up whenever all trust mechanisms are deactivated. *Distributors* and *Manufacturers* reach the bottom under the presence of *Lying Actors*, while *Retailers* and *Wholesalers* hit it without their appearance.

Evaluating both the Table 8 and the Figure 1 further, it becomes apparent that the $TVAmp$ value is rising for each trust mechanism getting deactivated. So (as described above) the Bullwhip effect is the weakest during the presence of trust, indirect trust and information sharing. Deactivating information sharing results in the biggest leap of the $TVAmp$ values. For the experiment without *Lying Actors* it on average across all actors increases by 162%, which to a large degree is based on the 202% increase of the $TVAmp$



(a) *TVAmp* Retailer. (b) *TVAmp* Wholesaler. (c) *TVAmp* Distributor. (d) *TVAmp* Manufacturer.

Figure 1: Bullwhip-Effect visualized for the different Actors.

Table 6: Verification based on average bullwhip values with deactivated information sharing.

	Retailer	Wholesaler	Distributor	Manufacturer
(Dejonckheere et al., 2004)	1.67	2.99	5.72	11.43
(Chatfield et al., 2004)	2.22	5.21	11.51	23.77
(Chatfield and Pritchard, 2013)	2.23	5.21	11.39	23.31
Results	1.49	2.35	3.41	11.70

value for the *Wholesaler*. In the presence of *Lying Actors* the shift is less extreme, with an average increase of 48% which is much more evenly distributed across the separate actors. Disabling the direct trust and indirect trust further exhibits further negative influence on the *TVAmp* score, however, the influence degree is much smaller. So the overall increase of the Bullwhip effect is at about 199% without *Lying Agents* and about 65% for cases with such agents.

Comparing Figures 1(a) and 1(b) to the Figures 1(c) and 1(d) further reveals that the BWE impacts *Retailer* and *Wholesaler* worse with no *Lying Actor* included. *Distributor* and *Manufacturer*, however, are mostly affected whenever such liars are present.

Analyzing the effects within one (actor to actor) test case indicates that the strongest increase of the BWE occurs between *Retailer* and *Wholesaler*. There the *TVAmp* value rises by 590% on average. Between *Wholesaler* and *Distributor* the average increase with 332% is still high. In the presence of *Lying Agents* increase is about 497%, whereas cases without them only increase by 168%. This difference in *TVAmp* value impact caused by the *Lying Agents* can similarly be observed looking at the supply chain from beginning to end: SCs free of liars (test cases 1-4) exhibit an average BWE increase of 403%, while SCs affected by liars rise about 985% ($\sim$ twice as strong).

5 CONCLUSIONS

Based on an experimental trust examination over different dimensions, this paper was successful in using created insights to support decision making in order to reduce the BWE. Due to the scarcity of trust related supply chain data a gamified web-based trust behavioral experiment was devised.

The conducted three stepped experiment lead to the following observations: Step one was able to uncover three major procurement profiles regarding the three dimensions *price*, *delivery time* and *trustworthiness*. In step two the trust profiles for the previously identified groups were established. Beside the insight that for most people the dimensions of *Competence*, *Reliability* and *Quality* were of equal importance, it proved to be a useful cross-validation tool as well: One group valuated *Delivery Time* lowest in it's procurement profile. Once price was out of consideration (e.g. in the trust evaluation), the same group valuated *Reliability* highest. This contradicts their low assessment of *Delivery Time* since both are very similar constructs (see Section 3). Furthermore a set of trust information sharing thresholds has been discovered.

The acquired data was used to initialize the different agents in the developed simulation model. The special focus has been to align the newly created simulation model with existing analytical SC models. For a more realistic scenario the lying actors concept was introduced, enabling existing actors to exhibit opportunistic behavior.

Furthermore it was possible to show the importance of trust in the procurement and ordering decision-making. The simulation experiment results revealed that under the influence of trust, indirect trust and information sharing the BWE is weakened. This finding confirms the already existing theoretical ideas from the supply chain literature where these concepts have been identified as countermeasures for the BWE (Moyaux et al., 2007). Additionally it was possible to confirm existing believes about the difficulties of mitigating damaged trust relationships (Kim et al., 2006).

The Trust Behavioral Experiment has some limita-

Table 7: Verification based on average Bullwhip values with activated information sharing.

	Retailer	Wholesaler	Distributor	Manufacturer
(Dejonckheere et al., 2004)	1.67	2.61	3.83	5.32
(Chatfield et al., 2004)	2.22	3.89	5.76	7.62
(Chatfield and Pritchard, 2013)	2.23	3.91	5.78	7.65
Results	1.38	2.11	2.92	10.89

Table 8: Bullwhip-Effect Values of the Validation Test Cases. Legend: Test Case (TC), Retailer (R), Wholesaler (W), Distributor (D) and Manufacturer (M).

	Bullwhip-Effect Values			
TC	R	W	D	M
1	2.6654	8.4928	19.8690	67.1102
2	3.6357	25.6233	71.5803	167.4304
3	3.9001	28.1745	79.3702	187.4566
4	4.1932	29.1924	81.1145	191.8513
5	1.2600	10.1519	54.5839	140.3891
6	1.9001	14.5047	90.5963	190.2219
7	2.0574	16.0391	96.8988	194.5419
8	2.1879	16.1255	99.9479	201.4702

tions. First results show that some participants seem to assess received orders more randomly or rate dimensions without considering delay or quality. Ambiguous explanations of that assessment or missing background knowledge could be reasons for that. Potential fixes would be raising demographic data, giving personal, introductory briefings or experimenting with practitioners. Furthermore the sample size is relatively small, yet sufficient to gain initial results. Although not incorporated in this paper, current research is taking place in order to increase participation by improving the gaming experience. Additional dimensions is also being considered.

Despite the fact that additional research is still necessary, the preliminary results presented here revealed that the use of computational trust mechanisms can be helpful to reduce the Bullwhip Effect.

REFERENCES

Abdul-Rahman, A. and Hailes, S. (2000). Supporting trust in virtual communities. In *System Sciences, 2000. Proceedings of the 33rd Annual Hawaii International Conference on*, pages 9–pp. IEEE.

Argonne National Laboratory (2015). Repast.

Ba, S. and Pavlou, P. A. (2002). Evidence of the Effect of Trust Building Technology in Electronic Markets: Price Premiums and Buyer Behavior. *MIS Quarterly*, 26(3):243–268.

Ba, S., Whinston, A. B., and Zhang, H. (2003). Building Trust in Online Auction Markets Through an Economic Incentive Mechanism. *Decision Support Systems*, 35(3):273–286.

Bachmann, R. (2001). Trust, Power and Control in Trans-Organizational Relations. *Organization Studies*, 22(2):337–365.

Braynov, S. and Sandholm, T. (2002a). Contracting With Uncertain Level Of Trust. *Computational Intelligence*, 18(4):501–514.

Braynov, S. and Sandholm, T. (2002b). Incentive Compatible Mechanism for Trust Revelation. In *Proceedings of the First International Joint Conference on Autonomous Agents and Multiagent Systems: Part 1*, pages 310–311, Bologna, Italy. ACM Press.

Burnett, C., Norman, T. J., Sycara, K., and Oren, N. (2014). Supporting trust assessment and decision making in coalitions. *IEEE Intelligent Systems*, 29(4):18–24.

Castelfranchi, C. and Falcone, R. (1998). Principles of Trust for MAS: Cognitive Anatomy, Social Importance, and Quantification. In *Proceedings International Conference on Multi Agent Systems (Cat. No.98EX160)*, pages 72–79. IEEE Comput. Soc.

Chaib-draa, B. and Müller, J. (2006). *Multiagent based supply chain management*, volume 28. Springer Science & Business Media.

Chatfield, D. C., Kim, J. G., Harrison, T. P., and Hayya, J. C. (2004). The Bullwhip Effect-Impact of Stochastic Lead Time, Information Quality, and Information Sharing: A Simulation Study. *Production and Operations Management*, 13(4):340–353.

Chatfield, D. C. and Pritchard, A. M. (2013). Returns and the bullwhip effect. *Transportation Research Part E: Logistics and Transportation Review*, 49(1):159–175.

Christopher, M. (1999). Logistics and supply chain management: Strategies for reducing cost and improving service financial times: Pitman publishing. london, 1998 isbn 0 273 63049 0 (hardback) 294+ 1× pp.

Clark, A. J. and Scarf, H. (1960). Optimal Policies for a Multi-Echelon Inventory Problem. *Management Science*, 6(4):475–490.

De Bruijn, H. and Herder, P. M. (2009). System and actor perspectives on sociotechnical systems. *IEEE Transactions on Systems, Man, and Cybernetics-Part A: Systems and Humans*, 39(5):981–992.

Dejonckheere, J., Disney, S., Lambrecht, M., and Towill, D. (2003). Measuring and avoiding the bullwhip effect: A control theoretic approach. *European Journal of Operational Research*, 147(3):567–590.

Dejonckheere, J., Disney, S., Lambrecht, M., and Towill, D. (2004). The impact of information enrichment on the Bullwhip effect in supply chains: A control engineering perspective. *European Journal of Operational Research*, 153(3):727–750.

Donohue, K. and Siemsen, E. (2011). Behavioral operations: applications in supply chain management. *Wiley Encyclopedia of Operations Research and Management Science*.

Forrester, J. W. (1958). Industrial dynamics: a major breakthrough for decision makers. *Harvard business review*, 36(4):37–66.

Gould, S. (2011). OpenForecast.

Greif, A., Milgrom, P., and Weingast, B. R. (1994). Coordination, Commitment, and Enforcement: The Case of the Merchant Guild. *Journal of Political Economy*, 102(4):745–776.

Ha, B.-C., Park, Y.-K., and Cho, S. (2011). Suppliers' affective trust and trust in competency in buyers: Its effect on collaboration. *International Journal of Operations & Production Management*, 31(1-2):56–77.

Haghpanah, Y. and DesJardins, M. (2010). Using a Trust Model in Decision Making for Supply Chain Management. In *Proceedings of the 3rd AAAI Conference on Interactive Decision Theory and Game Theory*, pages 25–29. AAAI Press.

Handfield, R. (2003). Trust in Supply Chain Relationships: What Does It Mean to Trust? - Part I.

Houser, D. and Wooders, J. (2006). Reputation in Auctions: Theory, and Evidence from eBay. *Journal of Economics & Management Strategy Management Strategy*, 15(2):353–369.

Kim, P. H., Dirks, K. T., Cooper, C. D., and Ferrin, D. L. (2006). When more blame is better than less: The implications of internal vs. external attributions for the repair of trust after a competence-vs. integrity-based trust violation. *Organizational Behavior and Human Decision Processes*, 99(1):49–65.

Kim, W.-S. (2009). Effects of a trust mechanism on complex adaptive supply networks: An agent-based social simulation study. *Journal of Artificial Societies and Social Simulation*, 12(3):4.

Kwon, I.-W. G. and Suh, T. (2005). Trust, commitment and relationships in supply chain management: a path analysis. *Supply chain management: an international journal*, 10(1):26–33.

La Londe, B. J. and Masters, J. M. (1994). Emerging Logistics Strategies: Blueprints for the Next Century. *International Journal of Physical Distribution & Logistics Management*, 24(7):35–47.

Laeequddin, M., Sahay, B. S., Sahay, V., and Waheed, K. A. (2010). Measuring trust in supply chain partners' relationships. *Measuring Business Excellence*, 14(3):53–69.

Lin, A. F.-r., Sung, Y.-w., and Lo, Y.-p. (2005). Effects of Trust Mechanisms on Supply-Chain Performance: A Multi-Agent Simulation Study. *International Journal of Electronic Commerce*, 9(4):91–112.

Marsh, S. P. (1994). *Formalising Trust as a Computational Concept*. Disseration, University of Stirling.

Mentzer, J. T., DeWitt, W., Keebler, J. S., Min, S., Nix, N. W., Smith, C. D., and Zacharia, Z. G. (2001). Defining Supply Chain Management. *Journal of Business Logistics*, 22(2):1–25.

Morgan, R. M. and Hunt, S. D. (1994). The Commitment-Trust Theory of Relationship Marketing. *Journal of Marketing*, 58(3):20–38.

Moyaux, T., Chaib-draa, B., and D'Amours, S. (2007). Information sharing as a coordination mechanism for reducing the bullwhip effect in a supply chain. *IEEE Transactions on Systems, Man, and Cybernetics, Part C (Applications and Reviews)*, 37(3):396–409.

Ottens, M., Franssen, M., Kroes, P., and Van De Poel, I. (2006). Modelling infrastructures as socio-technical systems. *International Journal of Critical Infrastructures*, 2(2-3):133–145.

Özer, Ö., Zheng, Y., and Chen, K.-Y. (2011). Trust in Forecast Information Sharing. *Management Science*, 57(6):1111–1137.

Pinyol, I. and Sabater-Mir, J. (2013). Computational trust and reputation models for open multi-agent systems: a review. *Artificial Intelligence Review*, 40(1):1–25.

Raimondo, M. A. (2000). The measurement of trust in marketing studies: a review of models and methodologies. In *16th IMP-conference, Bath, UK*. Citeseer.

Resnick, P. and Zeckhauser, R. (2002). Trust Among Strangers in Internet Transactions: Empirical Analysis of eBay's Reputation System. In Baye, M. R., editor, *Advances in Applied Microeconomics*, number 11, pages 127–157. Emerald Group Publishing Limited.

Ring, P. S. and Van de Ven, A. H. (1994). Developmental processes of cooperative interorganizational relationships. *Academy of management review*, 19(1):90–118.

Rousseau, D. M., Sitkin, S. B., Burt, R. S., and Camerer, C. (1998). Not so different after all: A cross-discipline view of trust. *Academy of management review*, 23(3):393–404.

Sabater, J. and Sierra, C. (2005). Review on Computational Trust and Reputation Models. *Artificial Intelligence Review*, 24(1):33–60.

ServiceNow (2016). % of undamaged goods after shipping/transportation.

Tykhonov, D., Jonker, C., Meijer, S., and Verwaart, T. (2008). Agent-based simulation of the trust and tracing game for supply chains and networks. *Journal of Artificial Societies and Social Simulation*, 11(3):1.

Yu, B. and Singh, M. P. (2002). An Evidential Model of Distributed Reputation Management. In *Proceedings of the First International Joint Conference on Autonomous Agents and Multiagent Systems: Part 1 - AAMAS '02*, pages 294–301, Bologna, Italy. ACM Press.

Yu, H., Shen, Z., Leung, C., Miao, C., and Lesser, V. R. (2013). A survey of multi-agent trust management systems. *IEEE Access*, 1:35–50.

Zacharia, G., Moukas, A., and Maes, P. (2000). Collaborative reputation mechanisms for electronic marketplaces. *Decision Support Systems*, 29(4):371–388.