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Implications of implementing industrial symbiosis for supply chain dynamics

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Abstract:
Industrial symbiosis has been recognized as a promising strategy to move towards a Circular Economy. However, its impact on the supply chain dynamics is still unexplored. For this reason, with this work we aim to contribute to this research gap analysing the dynamic performance of symbiotic supply chains. Through the agent-based modeling technique, we study two identical three-echelon supply chains, where there is a symbiotic exchange of waste between two manufacturers. We analyse a set of scenarios based on different demand/supply trade-offs and lead time of the treatment process for the waste, and evaluate them in terms of bullwhip effect. Based on our results, we state that the volume of order decreases with the increase of the symbiotic flow, while the order variability increases with it. Our findings suggest that, under certain conditions, symbiotic supply chains can turn into self-contained systems.

Keywords: Symbiotic Supply Chains, Bullwhip Effect, Industrial Symbiosis, Supply Chain Dynamics, Circular Economy, Agent-based Modeling Simulation

1. INTRODUCTION

Firstly defined by Chertow (2000) as part of the Industrial Ecology field, Industrial Symbiosis (IS) involves resource exchange between separate firms in a collective approach, whose purpose is the substitution of primary inputs of production processes, such as raw materials, by waste and/or by-products of other processes. IS practice, reducing the need to purchase from traditional suppliers (Chertow, 2000; Yazan et al., 2016), improves the sustainability of resource use (Rosado and Kalmykova, 2019; Yu and Yan, 2021). For this reason, IS adoption results a great opportunity to move towards the Circular Economy (CE) paradigm. CE, being restorative and regenerative by intention and design (Ellen MacArthur Foundation, 2013), aims to reach a zero-waste system where products and materials that flow across supply chains (SC) are meant to have several lives. Thus, to align with the CE principles, SCs should include mechanisms for materials and energy recovery, and by-products and waste reduction (Yazan et al., 2016).

As a consequence, from the SC perspective, IS introduces new relationships between previously unrelated companies (Herczeg et al., 2018). Firms in traditional SCs typically interact only with other companies upstream and/or downstream, while those involved in IS form a dense network of interdependent firms (Bansal and Mcknight, 2009). Therefore, the notion of symbiotic SC (SSC) (Turken et al., 2020; Turken and Geda, 2020) includes new symbiotic relations as well as resource and information sharing. Although IS has become a hot topic for academics and an attractive business opportunity for managers (see e.g. Fraccascia, 2019; Maranesi and De Giovanni, 2020; Chertow et al., 2021), currently only limited research has explored the role of IS in relation to SC sustainability development (Leigh and Li, 2015). Specifically, IS research at the operational level is scarce (Castiglione and Alfieri, 2019; Sehnem et al., 2019) and temporal dynamics have not been addressed (Herczeg et al., 2018). For instance, the phenomenon of orders fluctuations along the SC, known as Bullwhip Effect (BE) (Forrester, 1961) –that is one of the most widely investigated phenomena in SC research

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(Nepal et al., 2012)– has not been explored yet in the SSC context.

Motivated by the above-mentioned considerations, with this work we aim to fill the existing gap and to contribute to the literature on SSC dynamics by analysing their dynamic behaviour. More specifically, we model two traditional three-echelon forward SCs (FSC) that implement IS mechanisms at the manufacturer level, i.e. one manufacturer (denoted as *Waste Consumer*) exploits the waste generated by the other (denoted as *Waste Provider*) as new inputs, i.e. it substitutes the traditional inputs of the forward flow with waste coming from the symbiotic flow. We analyse the impact of two variables: (a) The *coefficient of circularity*, i.e. a proportional factor that relates the mean final customer demand in the two FSC in order to model the supply/demand trade-off, which has been identified as one of the main sources of uncertainty in IS settings that need to be overcome (see e.g. Herczeg et al., 2018; Fraccascia, 2019; Fraccascia et al., 2020; Neves et al., 2020; Kosmol et al., 2021), and (b) The *waste treatment lead time*, i.e. the time required to make the waste suitable as new inputs for the SC member that will use them in place of the virgin ones. To do so, we use Agent-Based Simulation Model (ABSM) as methodological approach, which has been widely used in the SC literature, see e.g. Dominguez et al., 2018; Ponte et al., 2017, and that has been recently adopted to advance the knowledge in the IS field (Fraccascia et al., 2019; Guedes et al., 2019). Adopting a Design of Experiments (DoE) approach, we compare these scenarios with the traditional FSC scenario in terms of commonly used metrics to detect the BE, focusing on the Waste Consumer. Among our findings, we describe how the final customers demand in SSCs influences the BE, and it impacts both orders' magnitude and variability.

The rest of this paper is structured as follows. Section 2 explains the developed model and the modelling assumptions. Section 3 describes the DoE and the performance metrics. Section 4 presents the numerical results and the discussion. Then, Section 5 summaries the obtained findings and managerial implications. Finally, Section 6 states the conclusions and future research.

2. SUPPLY CHAIN MODEL

This paper aims to study the implementation of IS between two manufacturers and the dynamic effect on their corresponding SCs, as depicted in Figure 1. Specifically, our model consists of two traditional FSCs (k=I,II), both consisting of a supplier, a manufacturer, a retailer (i=0,1,2), and an external customer, based on the well established model of Chatfield et al., 2004. The manufacturer of SC II, i.e. the Waste Provider, to fulfill its incoming demand, generates wastes and sends them, after a waste treatment process, T, to the manufacturer of SC I, i.e. the Waste Consumer, that uses them as new inputs. Since, to the best of our knowledge, there are no prior studies on the dynamic behaviour of the SSC, we build our model based on noted assumptions from the SC dynamics literature and adapt them to the SSCs setting as follows. Firstly, we describe in detail the modelling assumptions concerning the forward process, and secondly those related to the symbiotic one.

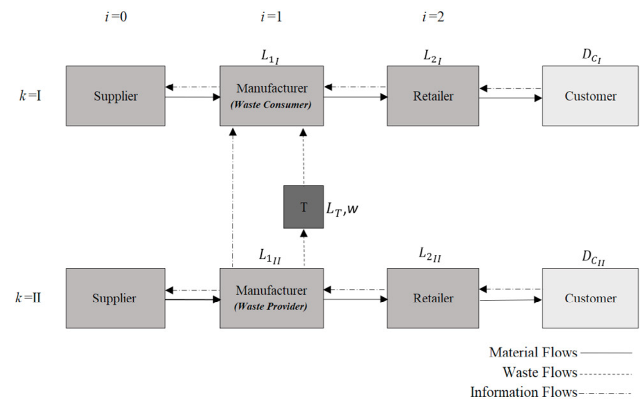

Fig. 1. SSC structure

2.1 Assumptions for the forward process

- *Demand, Lead Times and Forecasting.* Customers demands (D_{C_k}) and lead times for the forward flows (L_{i_k}) are assumed stochastic, independent and identically distributed (i.i.d.) variables as in similar studies, e.g. Chatfield et al., 2004; Cannella et al., 2017; Dominguez et al., 2020. D_{C_k} follows a normal distribution with mean $\mu_{D_{C_k}}$ and variance $\sigma^2_{D_{C_k}}$, while L_{i_k} follows a gamma distribution with mean $\mu_{L_{i_k}}$ and variance $\sigma^2_{L_{i_k}}$. We assume that the incoming demand is forecast using p-period moving averages and moving variances denoted by MA(p) and MV(p) respectively, while an all-data approach is used to forecast the estimated lead times.
- *Ordering policies.* We assume the Order-Up-To (OUT) periodic-review as ordering policy. Every time unit, SCs members compute the desired OUT level $S^t_{i_k}$ to meet the demand during the protection period $\overline{L}^t_{i_k} + R$, where R is the review period and they place orders as follows:
$$O^t_{i_k} = S^t_{i_k} - I^t_{i_k} - WIP^t_{i_k} + B^t_{i_k} \quad (1)$$
where $I^t_{i_k}$ is the current inventory, $WIP^t_{i_k}$ the inventory on order but not yet arrived (or work-in-progress) and $B^t_{i_k}$ the backlog. Using the demand data and the lead time data from previous periods, each member forecasts the average lead-time demand $X^t_{i_k}$ and computes $S^t_{i_k}$ as follows.
$$S^t_{i_k} = \overline{X}^t_{i_k} + z \cdot s^t_{X_{i_k}} \quad (2)$$
where
$$\overline{X}^t_{i_k} = (\overline{L}^t_{i_k} + R) \cdot \overline{D}^t_{i_k} \quad (3)$$
$${s^t_{X_{i_k}}}^2 = (\overline{L}^t_{i_k} + R) \cdot {s^t_{D_{i_k}}}^2 + \overline{D}^t_{i_k} \cdot s^t_{L_{i_k}} \quad (4)$$
Here, z is a safety factor, $\overline{D}^t_{i_k}$ and $s^t_{D_{i_k}}$ are the estimates of the mean and standard deviation of incoming demand, $\overline{L}^t_{i_k}$ and $s^t_{L_{i_k}}$ are the estimates of the mean and standard deviation of the lead times.

2.2 Assumptions for the symbiotic process

Here we adapt some assumptions used in closed-loop SCs (CLSC) related to the reverse flow of returns to the symbiotic flow of waste, see e.g. Hosoda and Disney, 2018 and Ponte et al., 2020a for the push policy.

- *Waste generation and Treatment process.* The volume of waste produced by the Waste Provider W^t is a function of the volume of output produced at time t, i.e. the demand satisfied, $W^t = w \cdot SD_{2_{II}}^{t}$, where w is a technical coefficient denoting the adopted production technology that quantifies how many waste units are generated to produce one output unit (Fraccascia, 2019). We assume that a waste treatment process T (Fraccascia, 2019) is required to make waste usable as input for the Waste Consumer as if were new input from the forward flow, so products coming from both flows can be used by the Waste Consumer to satisfy its incoming demand. A deterministic lead time L_T with mean μ_{L_T} to model the lead time of the treatment process is associated to T. We assume that L_T includes both the times required for transportation and processing, in order to model both the geographical proximity and the treatment process effort.
- *Push policy and information transparency.* We assume that all products exiting the treatment process are sent to the Waste Consumer (push policy), as it is in line with the principles of sustainability (Ponte et al., 2020a). Moreover, information on the treatment process is available for the Waste Consumer so it can be used to improve the estimation of the OUT level. Specifically, the Waste Consumer uses the waste work-in-progress WIP_W and the treatment lead times μ_{L_T} to compute its OUT level.
- *Coefficient of circularity.* Since the waste flow depends on the orders that the Waste Provider receives from the retailer (which in turn depends on the final customer demand), it follows that the waste flow of the Waste Provider depends itself on the final customer demand. As the required input by the Waste Consumer depends on its final customer demand too, it is clear that different IS scenarios can be devised depending on the fraction of the input required by the Waste Consumer that can be provided by the Waste Provider, both in terms of the customer demands of their respective SCs. Thus, we model this feature using what we denote as the *coefficient of circularity* a, defined as $a = w \cdot \frac{\mu_{D_{C_{II}}}}{\mu_{D_{C_I}}}$. Values of a close to 1 represent system where (on average) all the input required by one SC can be provided by the other, whereas low values of a represent less symbiotic scenarios where a higher proportion of external inputs are needed (e.g. $a = 0$ represents a traditional FSC).

2.3 Sequence of events

Each time unit t, after the demand generation by the customers $D_{C_k}^{t}$, each member in each SC (starting downstream to upstream) performs the following sequence of actions:

(1) Update $S_{i_k}^{t}$ based on the forecast made in the previous time unit.
(2) Place an order $O_{i_k}^{t}$ to bring the inventory position to the new value of $S_{i_k}^{t}$, i.e. update $WIP_{i_k}^{t}$ accordingly.
(3) Receive products from the upstream member, i.e. update $I_{i_k}^{t}$ and $WIP_{i_k}^{t}$ accordingly.
   - The Waste Consumer in addition receives products W^t from the Waste Provider, i.e. updates $I_{1_I}^{t}$ and $WIP_{1_I}^{t}$ accordingly.
(4) Satisfy (fully or partially) backlogs from inventory and update $I_{i_k}^{t}$ and $B_{i_k}^{t}$ accordingly.
(5) Receive a new incoming demand from the downstream member $D_{i_k}^{t}$, satisfy the demand (fully or partially) $SD_{i_k}^{t}$ and update $I_{i_k}^{t}$ and $B_{i_k}^{t}$ accordingly.
   - The Waste Provider in addition sends its waste W^t to a treatment process and then the information to the Waste Consumer that update its $WIP_{1_I}^{t}$.
(6) Update the forecast of incoming demand and lead times that will be used for $t + 1$.

3. EXPERIMENTAL DESIGN

In this section, we describe the experimental design, as summarized in Table 1 and Table 2, that is based on existing works, see e.g. Chatfield et al., 2004, Dominguez et al., 2020. We have adopted a full factorial Design of Experiments (DoE) approach, i.e. as commonly done in the SC dynamics field (see e.g. Ponte et al., 2020b; Cannella et al., 2021), to isolate the effects of interest, while some parameters remain fixed. As stated previously, we focus on the analysis of the coefficient of circularity a and the mean treatment lead time μ_{L_T}. Concerning the technical coefficient, w, it is assumed to be w=1 for all simulated scenarios, i.e. one unit of output generates one unit of waste. In addition, we simulate the a=0 scenario that represents the case of absence of symbiotic exchange, i.e. the traditional FSC scenario, as benchmark. We explore $5 \cdot 4 = 20$ scenarios, i.e. 21 considering the traditional FSC one. For each scenario, 20 replications have been performed, with a length of 3,500 periods with the first 2,000 removed as warm-up.

Table 1. Model Variables

a	Coefficient of circularity	0.5, 0.6, 0.7, 0.8, 0.9
μ_{L_T}	Mean treatment lead time	2, 4, 6, 8

Table 2. Model Parameters

w	Technical coefficient	1	
$\mu_{D_{C_k}}$	Mean customer demand	50	k=I
$cv_{D_{C_k}}$	Coefficient of variation for the customers demand	0.4	k=I,II
$\mu_{L_{i_k}}$	Mean forward lead times	4	k=I,II; $i = 0, 1, 2$
$cv_{L_{i_k}}$	Coefficient of variation for the forward lead times	0.25	k=I,II; $i = 0, 1, 2$
R	Review period	1	
z	Safety factor	2	
p	Forecasting period	15	

3.1 Key performance indicators

The selected key performance indicators ($KPIs$) that aim to detect the BE in our SSCs model are the order rate variance ratio, $OrVrR$, and its simplified version $OrVrR'$ that is by far the most widely used indicator to measure the BE (Cannella et al., 2013). They are computed as in (5) and (6), where O_{i_k} is the order at generic SC member i and D_{C_k} the final customer demand. When they are bigger than one, it indicates that there is an amplification, i.e.

there is BE. Specifically, they will be applied for the SC member that experiences the symbiotic exchange, i.e. the Waste Consumer. Therefore, for the sake of simplicity, in the following we denote $OrVrR = OrVrR_{1_I}$, $OrVrR' = OrVrR'_{1_I}$, $\sigma_O = \sigma_{O_{1_I}}$ and $\mu_O = \mu_{O_{1_I}}$. In addition, we discuss σ_O and μ_O and the coefficient of variation for the orders, i.e. $cv_O = \frac{\sigma_O}{\mu_O}$, to fully analyse the order stability of the system.

$$OrVrR_{i_k} = \frac{\sigma^2_{O_{i_k}}/\mu_{O_{i_k}}}{\sigma^2_{D_{C_k}}/\mu_{D_{C_k}}} \quad (5)$$

$$OrVrR'_{i_k} = \frac{\sigma^2_{O_{i_k}}}{\sigma^2_{D_{C_k}}} \quad (6)$$

4. NUMERICAL RESULTS AND DISCUSSION

Here we discuss the numerical results obtained. As mentioned, they are focused mainly on the Waste Consumer, that is the member of the SSC involved in the symbiotic exchange. Before discussing the $KPIs$ described in the previous section one by one, we analyse the order average μ_O, the standard deviation of the orders σ_O, and the coefficient of variation for the orders cv_O, referring to Table 3.

Firstly, we focus on the impact of the coefficient of circularity a. We observe that when its value increases, the order average decreases. More specifically, as we assume that one waste unit from the Waste Provider is used by the Waste Consumer to produce one unit of product, i.e. w=1, the two final mean customers demand are mainly related by the coefficient a. As a consequence, the order average reduction is related with a. For instance, when a=0.5 the μ_O is close to the 50% of the μ_O for the traditional FSC scenario, i.e. the 50% of the final customer demand average. However, μ_O values for symbiotic scenarios do not exactly coincide with the remaining ratio of the coefficient of circularity, i.e. $\mu_O \neq \mu_D \cdot (1 - a)$, due to the several sources of variability in our model, i.e. the variability of the final customers demands and the variability of the forward lead times. Similarly to the previous case, σ_O decreases as a increases. Interestingly, although both the order average and standard deviation decrease with a, the coefficient of variation increases with a, being always higher than in the traditional forward scenario ($a = 0$).

Moving to the $OrVrR$ metric, the BE in each scenario is higher than for the FSC. Due to the combined decrease of μ_O and σ_O, with the increase of cv_O, $OrVrR$ increases with a. As shown in 2, for all values of a, $OrVrR$ in symbiotic scenarios is higher than in the FSC. Contrarily, looking at the $OrVrR'$ as shown in 3, i.e. the simplified BE indicator that considers only order and demand variances, we observe an opposite trend, indeed it decreases as a increases. This result is foreseeable as a consequence of the above-mentioned order standard deviation reduction, i.e. order variance reduction.

Now we focus on the impact of different treatment lead times. In general, its impact is lower than that of the coefficient of variation. We observe that, as it increases, both $OrVrR'$ and $OrVrR$ increase. Its impact is lower

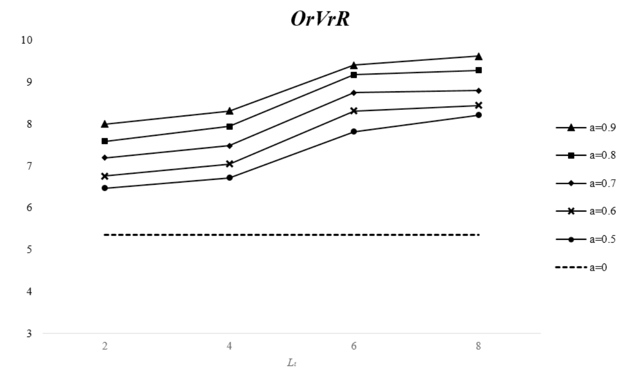

Fig. 2. Interaction of a and μ_{L_T} for $OrVrR$

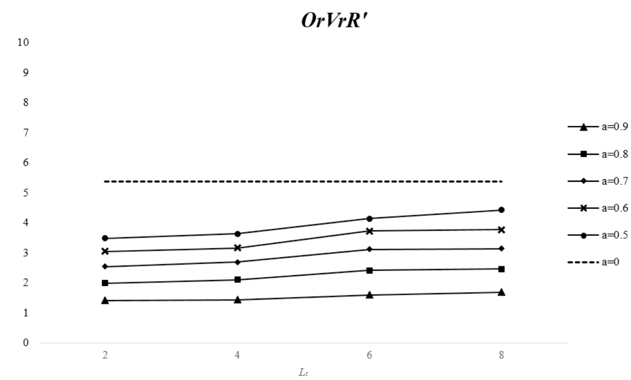

Fig. 3. Interaction of a and μ_{L_T} for $OrVrR'$

in the former KPI than in the latter, and it decreases when a increases, e.g. when a=0.9 it is slighter, while when a=0.5 it is more relevant. While for the latter KPI, it should be underlined that between μ_{L_T}=4 and μ_{L_T}=6 there is a higher increase compared to the increase between μ_{L_T}=2 and μ_{L_T}=4, and the one between μ_{L_T}=6 and μ_{L_T}=8. Noting that when μ_{L_T}=4 it coincides with the mean forward lead time, i.e. $\mu_{L_{i_k}}$=μ_{L_T}=4, the higher BE increase is observed when the treatment lead time overpasses the forward lead time.

Table 3. Numerical Results

			μ_O			
μ_{L_T} \ a	0	0.5	0.6	0.7	0.8	0.9
2	49.5±0.2	26.8±0.2	22.5±0.2	17.7±0.3	13.4±0.5	8.8±0.3
4		27.1±0.2	22.4±0.3	18±0.3	13.2±0.4	8.7±0.3
6		26.4±0.3	22.3±0.3	17.8±0.3	13.1±0.4	8.5±0.4
8		27.1±0.2	22.3±0.3	17.8±0.3	13.3±0.4	8.8±0.3
			σ_O			
μ_{L_T} \ a	0	0.5	0.6	0.7	0.8	0.9
2	46.1±0.4	37.3±0.4	34.9±0.4	31.9±0.4	28.7±0.8	23.7±0.4
4		38.2±0.4	35.5±0.4	32.8±0.4	29.1±0.6	24±0.6
6		40.6±0.6	38.5±0.6	35.3±0.6	31.1±0.7	25.3±0.6
8		42.1±0.5	38.8±0.5	35.4±0.5	31.4±0.6	26±0.6
			cv_O			
μ_{L_T} \ a	0	0.5	0.6	0.7	0.8	0.9
2	0.9	1.4	1.5	1.8	2.1	2.7
4		1.4	1.6	1.8	2.2	2.7
6		1.5	1.7	2.0	2.4	2.9
8		1.5	1.7	2.0	2.4	2.9

5. FINDINGS AND IMPLICATIONS

In this section, we summarize the contributions and provide some useful implications.

- *SC dynamic performance are affected by the implementation of the IS mechanism. In SSC, the SC* *member that receives the additional symbiotic flow of waste faces reduced orders average and variance and higher coefficient of variation for orders as compared to the traditional FSC.*

Based on our results, we can state that the dynamics of SSC are affected by the implementation of the IS mechanism. In particular, we focus our analysis on the member of the SC that is involved in the symbiotic exchange by receiving a symbiotic flow of waste coming from its mirror member in another identical SC. The existence of this new material flow implies several consequences that affect the operational behaviour of the involved SC member, which orders average, variance and coefficient of variation change depending on the final customer demand of the SC of the symbiotic partner. Moreover, concerning the BE evaluation, we observe contrasting trends depending on the selected performance metric. For this reason, we suggest to combine the traditional $KPIs$ for the operational performance of SC with specific ones for the symbiotic exchange. For instance, looking at the $OrVrR'$ it seems that as the coefficient of circularity increases, the manufacturer benefits from bullwhip reduction. On the contrary, if we look at the $OrVrR$, results suggest decreasing performance as the coefficient of circularity increases.

- *The waste treatment process lead time (μ_{L_T}) in SSC slightly impacts its performances compared to the coefficient of circularity (a).*

The match between available waste and required input represents an important challenge in IS settings (Kosmol et al., 2021), as well as geographical proximity. In our model, to analyse the former, we implement a proportional relation with the two final mean customers demands using a proportional factor, namely the coefficient of circularity. To model the latter, we defined a waste treatment process lead time that includes the transportation lead time, i.e. can be seen as a modeling for the geographical proximity. Based on our results, we can state that the coefficient of circularity strongly impacts the operational performance since it regulates the volume of waste. As it increases, the orders volume decreases both in terms of average and variance. Concerning the treatment lead time, its impact depends on if it is higher or lower than the forward lead time. However, its impact is marginal, which suggests that the geographical proximity and treatment process effort, from the operational perspective, slightly impacts SC performance as compared to the waste volume.

From a managerial point of view, our findings suggest that if firms aim to reduce orders' magnitude, the implementation of symbiotic exchange could be a good strategy to achieve this goal. Specifically, establishing symbiotic relations with SCs with final customers demands close to their one, or at least with a coefficient of circularity close to 1. However, it must be noted that in these cases the orders' variability increases. In addition, from a theoretical point of view, we stress the importance of selecting ad-hoc $KPIs$ to properly deal with SSCs and implement strategies that can reduce the BE. As we show that in SSC choosing one KPI or another may entail different conclusions, i.e. BE reduction or amplification compared to FSC. Finally, from a sustainability point of view, as orders from the FSC are reduced, the raw material consumption is reduced. It follows that SSCs make it possible to create systems that do not need external resources excepting those coming from the symbiotic exchange, i.e. no more orders from the forward SC, therefore to go towards a CE environment that is self-contained.

6. CONCLUSIONS

Nowadays, due to the increasing resource scarcity, companies need to overcome the linear "take-make-dispose" model and shift to a circular one that efficiently uses the available resources, so they must embrace the CE paradigm. The implementation of IS, where fewer resources are needed and less waste is produced, enables firms to align with CE principles. From the SC perspective, IS introduces new relationships between previously unrelated companies whose impact on the dynamic performance of the SC members has not been yet analysed. In this work, we analyse the effect of IS implementation on the dynamic performance of a SSC where exists a symbiotic exchange of waste between two manufacturers. We study the impact of the coefficient of circularity and the waste treatment lead time, focusing on the SC member that receives the waste flow. The results show that its dynamic behaviour is affected by the presence of the symbiotic exchange, as its order volume decreases and its order variability increases with the volume of waste. However, due to the additional material flows embedded in SSC, traditional BE $KPIs$ give contrasting results. Therefore, as future areas of research, we suggest the development of combined metrics that evaluate both the variability of order and the the variability of the symbiotic flow. Future studies could also focus on SSCs with waste inflow and outflow as well as complex networks such as intertwined supply network (ISN) (Ivanov and Dolgui, 2020).

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