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Technological Article

Pull Production Implementation: An Action Research Study

Implementando a Lógica de Produção Puxada: Uma Pesquisa-Ação

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ABSTRACT

Context: there is little empirical evidence of the relationship between the implementation of lean techniques (such as the pull system) and their real effect on supply chain performance. **Objective:** the purpose of this paper is to describe the process of implementing the pull production logic in the supply chain, reporting the historical evolution of indicators, such as inventory levels and lead times over 23 months of intervention. **Methods:** an action research project was carried out describing chain intervention steps in 2017-2019, divided into phases as follows: planning, data collection, implementation of the action, analysis and evaluation of the results. **Results:** the main contribution was to demonstrate that the production shift from push to pull had a positive impact on lead time, inventory, and planning routines indicators. Inventory levels were reduced by more than 30% and lead times were down approximately 40%. In addition, sales forecast assertiveness increased. **Conclusion:** this paper may provide a reference for organizations that want to make similar changes in their supply chains and significantly change the planning routine of their suppliers and distributors by implementing the pull logic.

Keywords: lean production; pull system; push system.

RESUMO

Contexto: existe pouca evidência empírica da relação entre a implementação efetiva de técnicas *lean* e o seu real efeito na performance da cadeia produtiva. **Objetivo:** o objetivo deste artigo foi descrever o processo de implementação da lógica de produção puxada na cadeia de suprimentos, relatando a evolução histórica dos indicadores associados à mudança, como os níveis de estoque e os *lead times* ao longo de 23 meses de intervenção. **Métodos:** foi conduzido um projeto de pesquisa-ação descrevendo os passos da intervenção na cadeia entre os anos de 2017, 2018 e 2019, dividida em fases: o planejamento, a coleta de dados, a implementação da ação, a análise e a avaliação dos resultados. **Resultados:** a principal contribuição foi demonstrar que a mudança de produção empurrada para puxada na pesquisa impactou positivamente os indicadores de *lead time*, estoque e rotinas de planejamento. Houve a redução de mais de 30% para os níveis de inventários e cerca de 40% para os *lead times*, além do aumento da assertividade da previsão de vendas. **Conclusão:** o artigo pode ser uma possível referência para organizações que queiram promover alterações semelhantes em suas cadeias de suprimentos e alterar de maneira significativa a rotina de planejamento de seus fornecedores e distribuidores através da implementação da lógica puxada.

Palavras-chave: produção enxuta; sistema puxado; sistema empurrado.

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INTRODUCTION

In today's competitive setting, with changes taking place at smaller and smaller intervals, it seems unlikely that operations area decisions triggering a manufacture order should be taken months before a product is received. Such a horizon may not be feasible, even when it comes to imported goods with all foreign trade procedures involved. The effects of lengthy lead times, which may be as much as a half year in some cases, may be magnified when a chain is involved, as illustrated by the bullwhip effect described in Forrester's (1958) and later revisited by Naim, Spiegler, Wikner and Towill (2017) or Nematollahi (2019). Such a magnification may harm business competitiveness.

The action research project that this paper describes aims to show how an actual case of supply chain discomfort became fertile ground for changing the way by means of which a company competes and carries out its procurement and delivery operations. This discomfort was represented by the six-month lead time the company had with one of the most important links on its supply chain, leading to inventory levels along the chain capable of compromising the future continuity of the business.

For the purposes of this paper, lead time is understood as the time needed between placing an order for an item and receiving said item. From the broad perspective of operations management, there are essentially two production logics that directly affect lead time: push logic and pull logic.

The push production logic is characterized by a leading business model based on sales forecasts, whereas one of the main traits of the pull production logic is increased responsiveness to sales, through production decision-making based on real-time demand behavior information, reducing the reliance of forecasts and the uncertainty that comes with it (Bowersox, Closs, & Cooper, 2020).

The pull production logic is a key pillar of the lean manufacturing system introduced in the mid-1990s by the seminal work of Jones, Roos and Womack (1990), and has been widely described in operations management literature (Danese, Manfe, & Romano, 2018; Tortorella, Miorando, & Marodin, 2017). There seems, however, to be a gap in terms of concrete examples of implementing the pull logic as a replacement for push logic, particularly concerning descriptions of the difficulties and gains that such a change causes for the entire chain.

Although the concept of pull production is usually connected with actual consumer demand, this paper embraces the definition of the pull system as a system pulled by actual demand from customers of a direct cosmetics sales company. These customers are sales consultants who, by their turn, resell the merchandise to end consumers. A push system is that in which production and procurement decisions are anticipated and based on internal sales forecasts, far earlier than the actual moment of sale to consultants.

According to the push logic, the entire planning and execution takes place anticipating sales forecasts, with sales estimates that often fail to come true. Under the pull logic, the production and procurement decision is triggered by sales to replenish the regulating inventory (supermarket) that the sale consumed. According to the pull logic, all phases are synchronized and lead times are reduced compared with the push system's phasing schedule (Bowersox et al., 2020; Danese et al., 2018).

For this article, the study initially observed a cosmetics company's production chain according to the push production logic. In this case, lead times were far too lengthy, in some cases taking more than six months from the moment at which the cosmetics company ordered goods from third-party manufacturers to the receipt of the respective products at its distribution hubs.

In the push logic production model, the cosmetics company triggered production orders to its third-party manufacturers based on sales forecasts for a certain month six months ahead of the moment when it would ship off the orders.

This much anticipation was needed because, upon receiving the order from the cosmetics company, the third-party manufacturer fired off orders for inputs that were often imported, with lead times of up to four months. Aside from the inputs procurement time, the third-party manufacturer needed approximately two months to manufacture the products, bringing the chain's total lead time to approximately six months.

Such lengthy lead times had consequences for the production chain, as they magnified the period during which sales forecasting uncertainty was considered for the purposes of procurement and production decisions, causing errors of up to 90% between sales forecasts and effective sales. These accumulated monthly, with reflections on the chains' inventory and service levels.

One of the most important consequences arising from this push production model with lengthy lead times and low sales forecast accuracy was a mismatch between inventory and demand levels, leading to a situation where average inventory levels were up to four times average monthly sales.

The difference was due to variations between demand forecasts at the time of the definition of a purchase order and actual sales taking place six months later.

The low accuracy of demand forecasts made with such anticipation, where accumulated errors caused misguided procurement and production decisions, led to inventory surpluses or deficits, in addition to a programming adjustments race to either postpone or expedite future deliveries, causing turbulence and changing production and procurement plans.

The lengthier this lead time, the more dependent the chain on demand forecasting accuracy. On the other hand, the closer the sales forecasts are to the moment of supply, the more efficient the operation is. Achieving improved demand forecasting accuracy is one of the greatest challenges that all companies and supply chain management professionals face, particularly given the consumer goods market's evolution and volatility (Angelo, Zwicker, Fouto, & Luppe, 2011).

Although the cosmetics market continues to transform and become more and more complex, be it due to new sales dynamics that the multichannel experience (retail, online, or direct sales) imposes, be it due to the increased variety of items on the portfolio because of the rising trend of customization in line with consumers' needs, most of the companies in the industry continue to use the push production system's conventional logic.

As noted earlier, a push production system's opposite is the adoption of a pull production logic, where production orders are only fired off when actual consumption in fact reduces inventory levels to a level that riggers a production order. The operations literature refers to such a model as a 'supermarket' system, where both the trigger inventory level and its ceiling and floor levels are predetermined so that the production chain operates with a given inventory sufficient to cover the time needed for replenishment (Zhang, Luo, Shi, Chia, & Sim, 2016).

The production logic that the supermarket system characterizes is one of the principles of the lean philosophy that drove the intervention this article proposes, where an experimental change was made to two of the company's SKUs to enable assessing the change's effects over time on the production chain.

The intervention's SKUs were chosen based on their strategic relevance to the company, and are produced at two different factories. The SKU made at the creams and lotions plant will be referred to as 'skincare cream', and the other SKU, made at a fragrances factory, will be referred to as 'fragrance'.

According to Bevilacquia, Ciarapica and De Sanctis (2017), companies must improve their processes to become more efficient, flexible, and agile in an increasingly challenging and complex market panorama. To this end, companies must implement processes that share information across the chain's participants to achieve the pull system concept and foster improved responsiveness to the market (Roh, Hong, & Min, 2014).

Little empirical relevance exists regarding implementation of lean techniques and the impacts thereof on the production chain as a whole (Näslund, 2013; Panwar, Jain, Rathore, Nepal, & Lyons, 2018; Roh et al., 2014; Tortorella et al., 2017). Many companies report the benefits of lean implementation, but many questions still stand on its applicability and on the concrete results found when applying the lean methodology to companies that do not match the characteristics of stable demand and lie in economically unstable markets rife with change.

This technology paper therefore aims to contribute to shedding light on this by addressing application of the pull system to an environment with unstable demand and constant changes, in addition to attempting to answer the following question: "'How can a production system change from push to pull in fact contribute to supply chain competitiveness?' Will there be significant changes in sales forecasting accuracy, lead time indicators, and inventory levels of a dyad made up of a cosmetics company and its third-party manufacturer?"

CONTEXT OF THE REALITY UNDER INVESTIGATION

At this point, it is important to note that one of this paper's authors was also the leading operations executive of the company at hand during the study, which facilitated both describing the context of the reality under investigation and access to data and all the developments that the research required.

Despite this privileged position, studying an industry's entire supply chain could be a risky task due to its potential extent and complexity, and possible dilution of the analytical focus. For this reason, the authors decided to limit the research, studying the dyad made up of a multinational company active in direct cosmetics sales and one third-party manufacturer (Mostafa, Dumrak, & Soltan, 2013).

Concerning the supply chain of the company under study in Brazil, 30% of its items are produced in a factory overseas and imported and distributed by its distribution hubs in various states.

As for the remaining 70% of items, the company undertook technology transfers so that the products concerned could be manufactured in Brazil by multinational partner manufacturers. Thus, products that are locally manufactured in Brazil abide strictly by quality, formulation, and production standards similar to those that the cosmetics company makes in its factories abroad.

To ensure the quality standards of locally made items in Brazil, the cosmetics company specifies the use of ingredients provided by global suppliers, most of which are located abroad. Only a few ingredients and components (packaging items, such as vials, labels, and boxes) are made by local suppliers.

Differently put, the cosmetics company specifies for the third-party manufacturer all of the items (ingredients, raw materials, packaging) to be used in its products. It is a previously defined arrangement governed by long-term agreements between the two agents to safeguard the cosmetics brand's worldwide quality standard.

Figure 1, next, shows a simplified depiction of the cosmetics supplies chain with manufacture entrusted to third parties in Brazil.

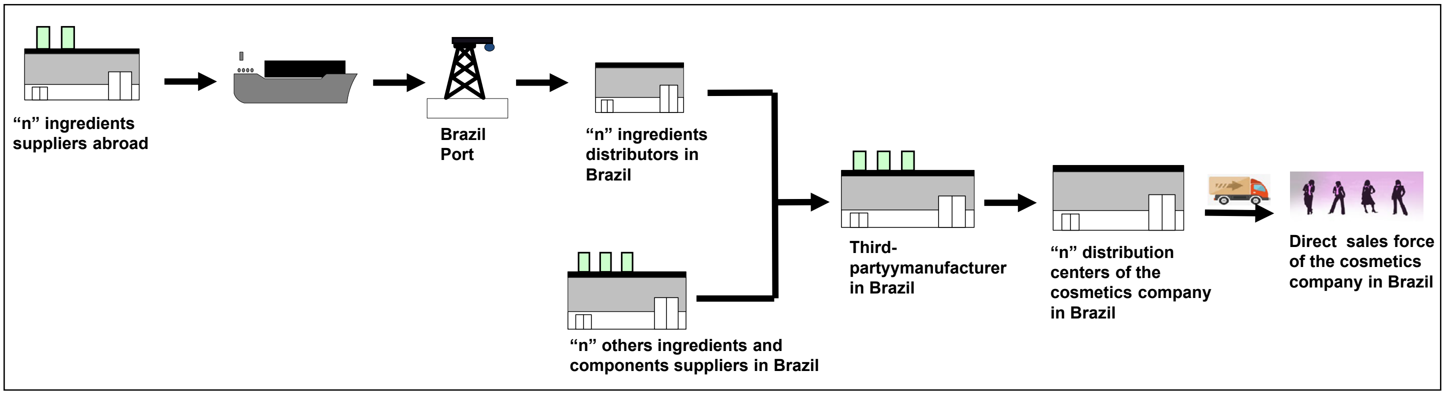

Figure 1. Supply chain of the cosmetics company in Brazil.
Source: Prepared by the authors.

Planning routine: understanding the company's push logic

The company traditionally works according to the push logic, in line with its activities schedule, with forecasts and programming. This anticipates demand from customers by means of sales forecasts (Liker, 2005; Nematollahi, 2019). To this end, the cosmetics company carries out monthly inventory planning routines, identifying product stocking needs, and programming its supply chains with third-party manufacturers and the respective inputs suppliers.

This push logic takes account of a sales forecast for the coming 12 months, the available inventory position at the cosmetics company's distribution hubs, and products undergoing production, that is, orders already placed with third-party manufacturers in previous months, but not yet delivered.

Internally, the senior inventories planning coordinator executes this routine in the first week of each month. After reviewing a report drawn from the cosmetics company's material requirements planning system, with information on inventories, sales forecasts, and orders placed with and awaiting processing by third-party suppliers, the coordinator determines the need to include new orders, and checks for the need to adjust orders already placed with third-party manufacturers. These adjustments to orders underway may be requests for anticipation, delivery prioritization, postponement, or even quantity restatements.

Both new orders and required adjustments to orders placed in previous months are reported to the cosmetics company's manufacturing manager, who is responsible for managing third-party manufacturers and for commercial relationships with them.

Also within the first week of each month, the manufacturing manager submits the requests to the third-party manufacturer and tracks the review thereof by the manufacturer, which normally responds within the second month of the week with confirmation of the inclusion of new orders into the schedule, as well as acceptance or refusal of requested adjustments to orders placed before.

Once the orders have been confirmed, the cosmetics company's manufacturing manager monitors the entire execution of the orders' processing to delivery at the cosmetics company's distribution hubs.

The entire production planning process is triggered based on sales forecasts, which characterizes the push production system, where decisions concerning inventory replenishment and placement of orders with third-party suppliers are based on sales forecasts and consider the total lead time for production and inputs supply from the moment when the cosmetics company confirms its production order with a third-party manufacturer.

According to the model, both input procurement and production orders are only fired off after an order from the cosmetics company. Upon receipt of a finished goods order from the cosmetics company, a third-party manufacturer will process its own material needs plan to fill the order, placing orders with local suppliers for domestic inputs and with distributors for inputs produced abroad.

These overseas suppliers take approximately four months to deliver the inputs to a third-party manufacturer, which, by its turn, needs another two months to manufacture and deliver the products to the cosmetics company. These phases, taken together, determine a total lead time of six months for the chain, from placement of an order by the cosmetics company with its third-party manufacturer to the delivery of the order.

This total lead time breaks down as Figure 2, below, shows.

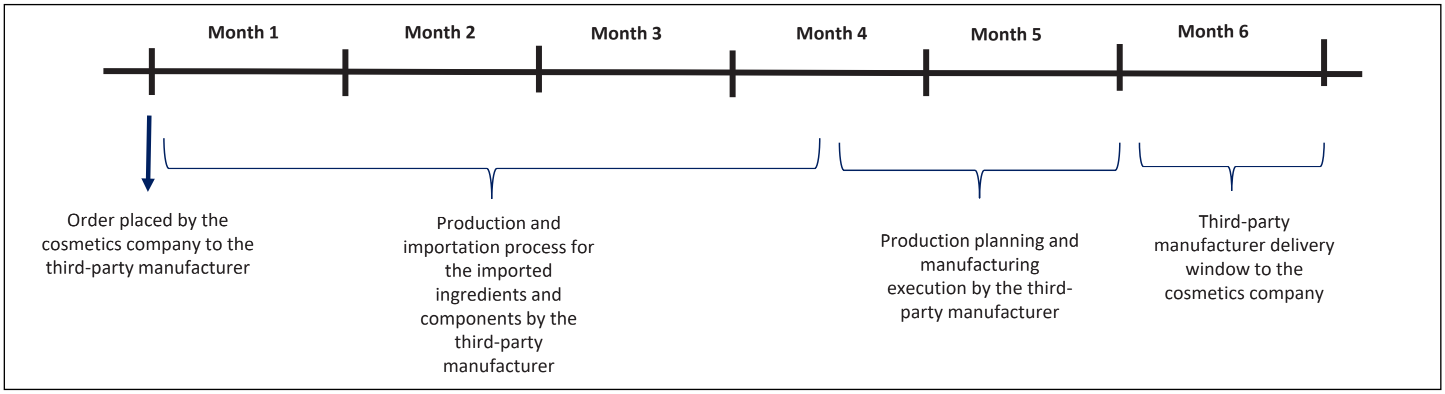

Figure 2. Supply chain lead times with third-party manufacturing.
Source: Prepared by the authors.

One of the main challenges that this supply chain faces is its responsiveness to variations in demand in the light of this lengthy six-month lead time. According to this push production model, the sales forecasts must be defined very much in advance, increasing the probability of misestimating sales because of the wide gap between the moment of the forecast and placing the respective order, and the moment when sales will in fact take place.

The mean accumulated error between forecast demand at order-placing time and effective sales six months after the order varied between 60% for the fragrance SKU and up to 90% for the skincare cream SKU, over a period of approximately one year during which the push logic was observed.

The main problems arising from this scenario include: (a) imbalanced inventories throughout the chain, with average inventories at about four times average sales volume; (b) frequent off-lead time orders and postponed delivery requests, leading to reworked production planning and programming; and (c) slow reaction to sales changes, as every order faced a total six months' lead time.

Demand forecasting errors were magnified as they were passed on upstream along the production chain (that is, from the point on the chain closest to the consumer toward the chain's initial end, where input makers are), increasing the negative consequences of inventory imbalances, creating a bullwhip effect (Forrester, 1958; Mbhele, 2018).

This situation of lengthy lead times and average inventories above average actual sales volumes as a result of the push system provides the investigation's original context.

METHODOLOGY

This technology study adopts the quantitative methodology, and its research strategy is action research. Adoption of the quantitative method is based on the nature of the subject of investigation, that is, an investigation on how a production change from push to pull may influence lead time and inventory indicators, and the accuracy of sales forecasts.

Selection of the action research method is due to the fact that this study chose to describe an intervention made on an outsourced production chain over a period of 23 months, where the earliest data are from October 2017 and the final month of analysis was August 2019, with one of the researchers acting as an executive and active participant in the intervention.

Action research has been standing out in scientific research in the production and operations engineering area (Mello, Turrioni, Xavier, & Campos, 2012). The supply chain management area is a vast field for research questions relevant to business managers, and action research focuses on the relevance of the subject at hand, addressing actual problems from the organizations' environment.

Action research differs from case studying because, in the latter case, the researcher is an observer that does not interfere with the subject of study, whereas action researchers interfere with their subject by interacting with the action's participants with the purpose of solving a problem and expanding the knowledge associated with the study (Dresch, Lacerda, & Miguel, 2015).

The main outputs of action research are action and research, unlike traditional positivist research, whose main purpose is to simply generate knowledge. An action research project is research in action, rather than research into action, with a participative approach focusing on solving a real-life problem (Coughlan & Coghlan, 2002).

The expected results of action research are not just solutions to problems, but learning from expected and unexpected outcomes, producing a contribution to scientific knowledge and theory. The results of positivist research are universal, whereas those created by action research are particular and situational. Despite being situational, the results of action research may be extrapolated to inform other organizations on how to act in connection with a specific problem (Dresch et al., 2015).

According to Mello, Turrioni, Xavier, and Campos (2012), action research comprises five phases: action research planning, data collection, data analysis, implementation of the action, and review of results. The five phases take place successively and cyclically, so that the outcome of an original cycle is reviewed and taken into consideration for the purposes of preparing the following cycle. Figure 3 shows the cyclical nature of action research phases.

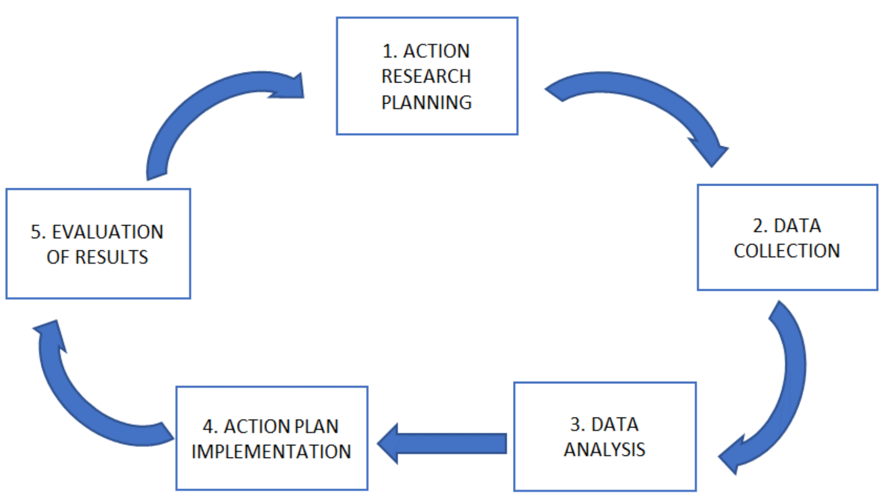

Figure 3. Phases of an action research project.
Source: Adapted from Mello et al. (2012).

The action research project proposed for this study follows this execution flow, as described next.

Action research planning

An action research project may begin with two alternative approaches: identification of a problem after a literature review and then pursuing a subject where the problem can be solved; or identifying a problem within an organization and giving researchers an opportunity to take part in solving the problem by applying the research method (Mello et al., 2012).

Planning of the action research effort for this applied paper adopted the latter approach, that is, identifying a problem situation at the cosmetics company, that is, the effects of the push system on an outsourced production chain with lengthy lead times, incurring forecasting errors that create imbalanced inventories relative to the sales volume, which hampers the chain's responsiveness and agility.

Based on this, the theoretical fundamentals are defined and the action research phases are structured. Figure 4 shows the action research approach adopted while planning the article, represented by the highlighted and scored figures below.

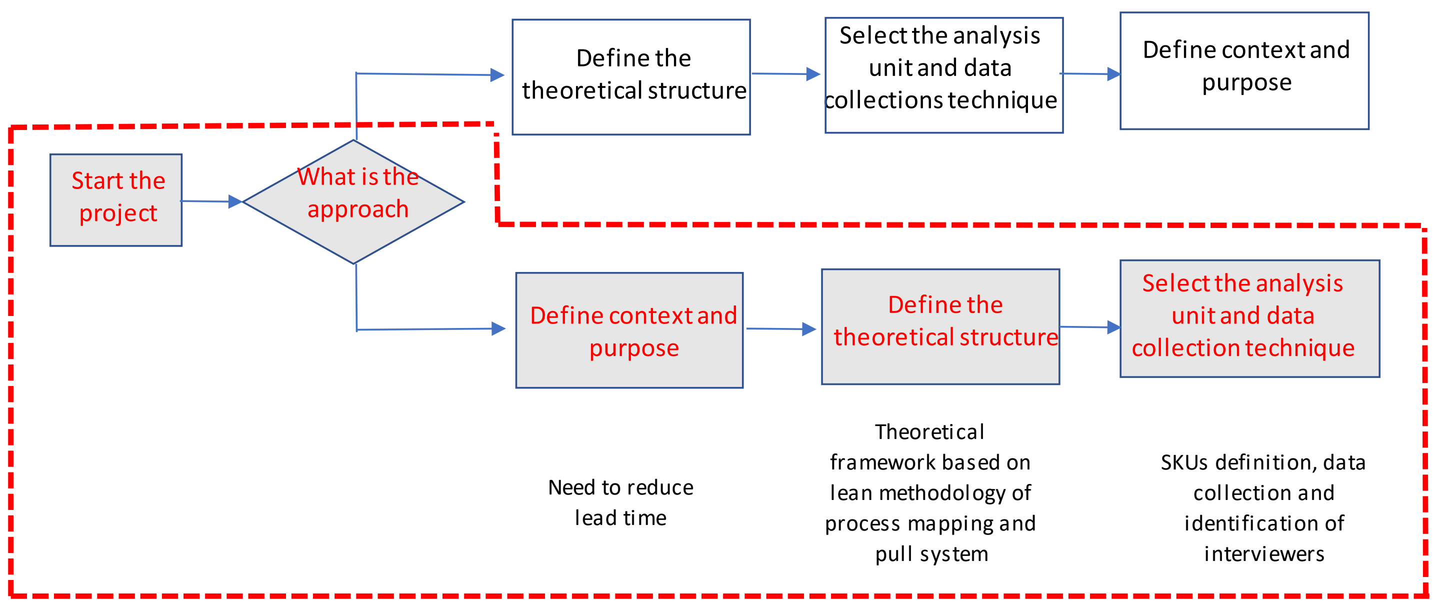

Figure 4. The paper's action research approach.
Source: Adapted from Mello et al. (2012).

One of the most important aspects of this action research project's planning was selection of the analytical unit, that is, the SKUs to be investigated. The intervention's selection criteria were the SKUs' strategic importance to the company and the ratio of monthly demand for the items to the minimum volume that the third-party manufacturer requires for each batch run.

The authors deliberately selected items whose minimum batch run was no more than three average months' average demand.

The reason for this was to avoid extended intervals between batch runs, that is, if an SKU's demand is far lower than the minimum batch that the third-party manufacturer requires, inventories would increase excessively after each receipt of an order triggered by the pull system, and it would take a long time to reach the next trigger point, that is, trigger frequency would be low.

On the other hand, with the rule that requires minimum production volume to be three months of average demand at the most, triggering will probably take place at intervals below three months.

According to these criteria, two of the cosmetics company's items were selected to determine the effects of a production system change from push to pull. Both items are made by the same third-party manufacturer, but at two different factories, one being a creams factory and the other a fragrances factory.

The selection of two items from different plants, undergoing different processes, was meant to enrich the evaluation of the pull system's implementation in two completely distinct and independent industrial environments, which required duplicating every effort in order to replicate the interventions.

Each selected item is made up of a series of components, with the respective inputs suppliers and/or distributors, which increases the intervention's complexity because it requires involving the participants in the production system change.

To simplify the analysis, the authors analyzed the ingredients and components exclusive to the finished item selected for the intervention, which produced the list provided in Table 1, below.

Table 1. Inputs breakdown for the intervention's subject SKUs.

SKU: Skincare Cream			
Input Type	Input	Local/Imported	Supplier/Distributor
Raw Material 1	Ingredient 1	Imported	Distributor 1
Raw Material 2	Ingredient 2	Imported	Distributor 2
Raw Material 7	Ingredient 7	Imported	Distributor 1
Raw Material 13	Ingredient 13	Imported	Distributor 1
Component 1	Cartridge	Local	Supplier 1
Component 8	Tube	Local	Supplier 8
SKU: Fragrance			
Input Type	Input	Local/Imported	Supplier/Distributor
Raw Material 2	Ingredient 2	Imported	Supplier 2
Component 1	Vial	Imported	Supplier 4
Component 2	Lid	Imported	Supplier 5
Component 3	Label	Local	Supplier 6
Component 4	Cartridge	Local	Supplier 7
Component 5	*Liner*	Local	Supplier 8
Component 6	Component	Local	Supplier 9
Component 7	Valve	Imported	Supplier 10

Note. Developed by the authors.

The intervention thus involved six items (including components and raw materials) for the cream SKU and eight for the fragrance SKU. The logic change from push to pull would directly affect the relationship with a total 10 direct suppliers (domestic and overseas) and three domestically located distributors.

Data collection: diagnosis of the problem and/or opportunity

Data for the action research project was collected in different ways, as recommended by Coughlan and Coghlan (2002). It includes the researchers' direct observations in the intervention environment, and soundings based on interviews with and inquiries of participants on interpretation of the operational data and impacts of the change.

Secondary data was gathered through documental analysis of reports from the cosmetics company's and its third-party manufacturer's procurement and inventory systems. For every finished item and the respective inputs selected at the intervention's analytical units, the authors collected historic inventory and order lead time data.

Data at the inventory level was also presented as inventory coverage indicators, that is, absolute inventory data was collected as units and converted into months' coverage, subtracting from the absolute inventory count the respective item's demand in subsequent months. This converts absolute inventories into inventory coverage (a months' inventory measuring unit) in the face of future demand.

For the relevant SKUs, that is, skincare cream and fragrance, sales forecasting data were collected at the time of order placement and upon effective sale, six months after the order, from October 2017 to November 2018, as Table 2 shows.

Table 2. Demand forecasting error under the push system.

SKU: Skincare Cream				
	Forecast Lag 6	Effective Sales	Absolute Error	% Error
oct/17	140,058	505,330	365,272	260.8%
nov/17	128,579	119,512	9,067	7.1%
dec/17	120,721	103,431	17,290	14.3%
jan/18	10,462	91,886	81,424	778.3%
feb/18	126,649	324,668	198,019	156.4%
mar/18	155,013	75,878	79,135	51.1%
apr/18	176,646	79,397	97,249	55.1%
may/18	135,843	79,004	56,839	41.8%
jun/18	138,277	103,420	34,857	25.2%
jul/18	125,377	80,013	45,364	36.2%
aug/18	134,866	456,425	321,559	238.4%
sep/18	116,055	64,012	52,043	44.8%
	1,508,547	**2,082,976**	**1,358,119**	**90%**
SKU: Fragrance				
	Forecast Lag 6	Effective Sales	Absolute Error	% Error
oct/17	5,116	10,745	5,629	110.0%
nov/17	59,757	28,157	31,600	52.9%
dec/17	10,139	14,889	4,750	46.9%
jan/18	6,600	10,517	3,917	59.3%
feb/18	27,425	9,263	18,162	66.2%
mar/18	43,053	12,992	30,061	69.8%
apr/18	24,061	10,887	13,174	54.8%
may/18	23,234	10,691	12,543	54.0%
jun/18	16,446	11,562	4,884	29.7%
jul/18	28,659	23,170	5,489	19.2%
aug/18	23,492	16,995	6,497	27.7%
sep/18	13,636	9,245	4,391	32.2%
oct/18	48,211	8,427	39,784	82.5%
nov/18	11,759	38,188	26,429	224.7%
	341,587	215,728	207,310	60.7%

Note. Developed by the authors.

In Table 2, the 'Forecast Lag 6' column represents forecast demand, in units, six months prior to sale. The 'Effective Sales' column represents actual sales taking place on the relevant month.

For the intervention's selected SKUs, the authors also collected data on lead time (in calendar days) for the cosmetics company's orders, comprising the time between the cosmetics company's placement of an order with the third-party manufacturer and the receipt of the respective products.

Table 3, next, shows data on lead times for the orders placed under the push system for the two SKUs at hand.

Table 3. Lead times on orders of the skincare cream and fragrance SKUs.

Lead Times – Push System		
	Skincare Cream	
Order Placement Day	Date of 1st Delivery	Time (Calendar Days)
03/20/17	9/20/17	184
06/27/17	11/8/17	134
07/21/17	12/4/17	136
08/22/17	1/8/18	139
09/19/17	2/5/18	139
10/19/17	3/14/18	146
12/22/17	6/11/18	171
05/03/18	9/20/18	140
	Average:	148.6
	Standard deviation:	18.5
	Fragrance	
Order Placement Day	Date of 1st Delivery	Time (Calendar Days)
05/05/17	10/16/17	164
09/25/17	01/24/18	121
09/25/17	01/24/18	121
10/13/17	03/12/18	150
12/21/17	06/05/18	166
02/19/18	08/03/18	165
	Average:	147.8
	Standard deviation:	21.6

Note. Prepared by the authors.

Analysis of the data: the problem situation

Sales forecasts

Under the push system, the study found that the mean error of sales forecasts is high because of the long time span between order placing and effective sale six months thereafter.

The mean error between forecast demand upon ordering and effective sale was approximately 90% for the skincare cream SKU over the 14 months from October 2017 to November 2018. The accumulated accuracy percentage was approximately 10% in the same period.

For the fragrance SKU, the mean accumulated demand forecasting error in the 14-month period from October 2017 to November 2018 was 60.7%, with accuracy consequently at 39.3%.

Lead times

The push system's lead times showed a wide gap between order placing and delivery.

In the case of the skincare cream SKU, the study collected lead time data for eight orders over a period of 18 months, from March 20, 2017 to September 20, 2018. Average lead time for the eight orders was 148.6 calendar days, with a standard deviation of 18.5 days.

For the fragrance SKU, data was obtained from six orders over a period of 15 months, from May 5, 2017 to August 3, 2018. Average lead time for these orders was 147.8 days, with a standard deviation of 21.6 days.

Inventory levels

In the push system scenario, the cosmetics company has finished goods inventories mismatched with sales behavior. Figure 5, next, illustrates this behavior for the skincare cream item.

The average start-of-month inventory of the skincare cream SKU under the push system was 672,224 units, approximately 3.8 times average monthly sales, which were 174,714 units. The average end-of-month inventory level was 610,258 units, and approximately 3.5 times average sales.

The push system's inventory coverage indicator shows average 4.0 months' coverage in stock. Figure 6, next, shows the coverage data.

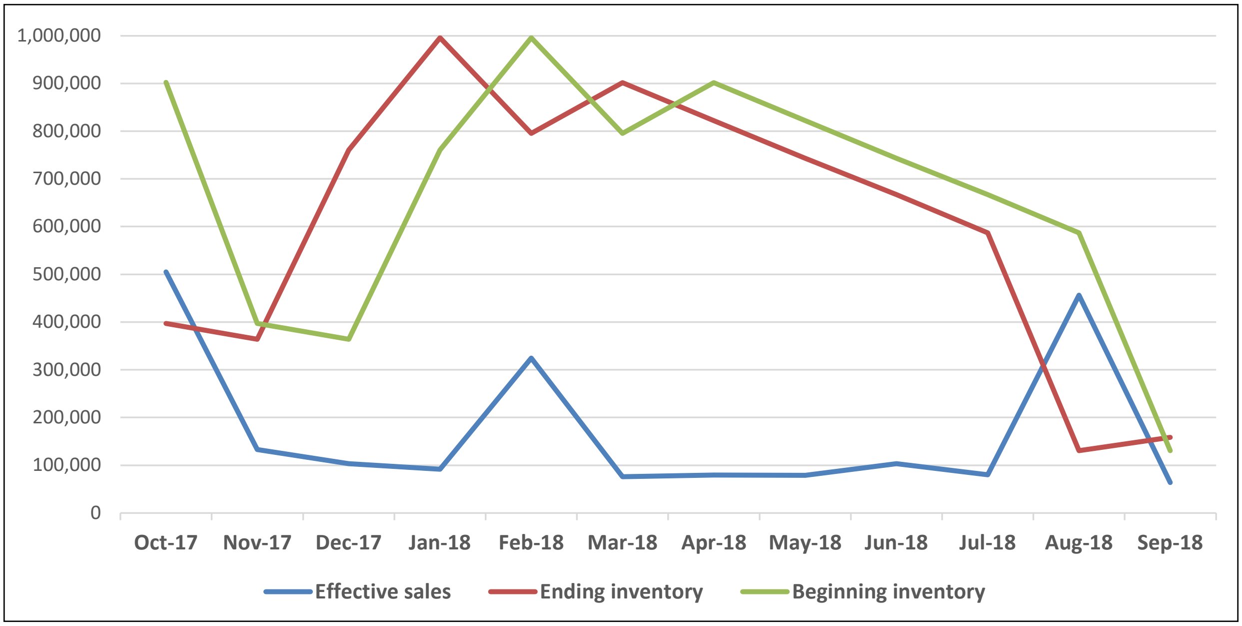

Figure 5. Push system inventories and sales — skincare cream SKU.
Source: Developed by the authors.

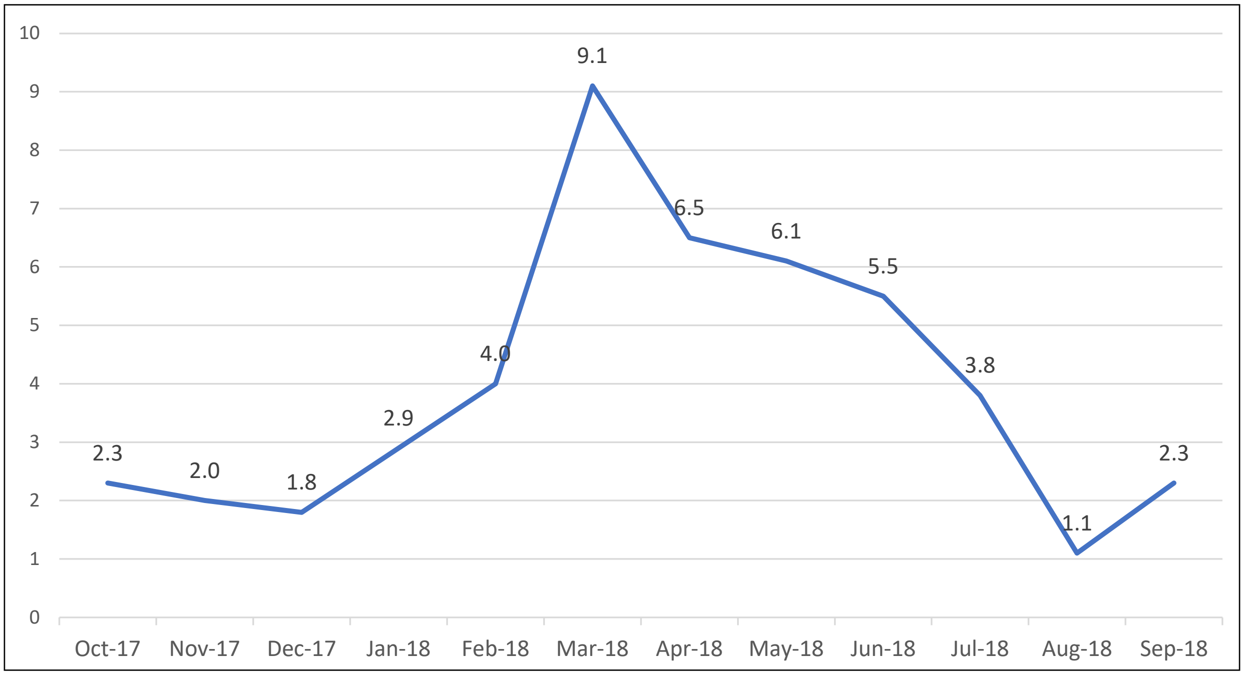

Figure 6. Cosmetics company's finished goods inventory coverage indicator — skincare cream SKU.
Source: Developed by the authors.

As for the third-party manufacturer's inventory coverage, the overall inputs inventory level, including ingredients and components, was an average 3.52 months' coverage under the push system.

Similar analyses were performed for the fragrance SKU. Figure 7, next, shows the mismatch between start-of-month and end-of-month inventories and monthly sales.

The average start-of-month stock of the fragrance SKU in this period was 58,828 units, at approximately 3.8 times average monthly sales, which was 15,409 units. The average end-of-month stock was 54,514 units, approximately 3.5 times average sales volume.

The push system's inventory coverage indicator shows average 3.3 months' coverage in stock, as Figure 8, next, shows.

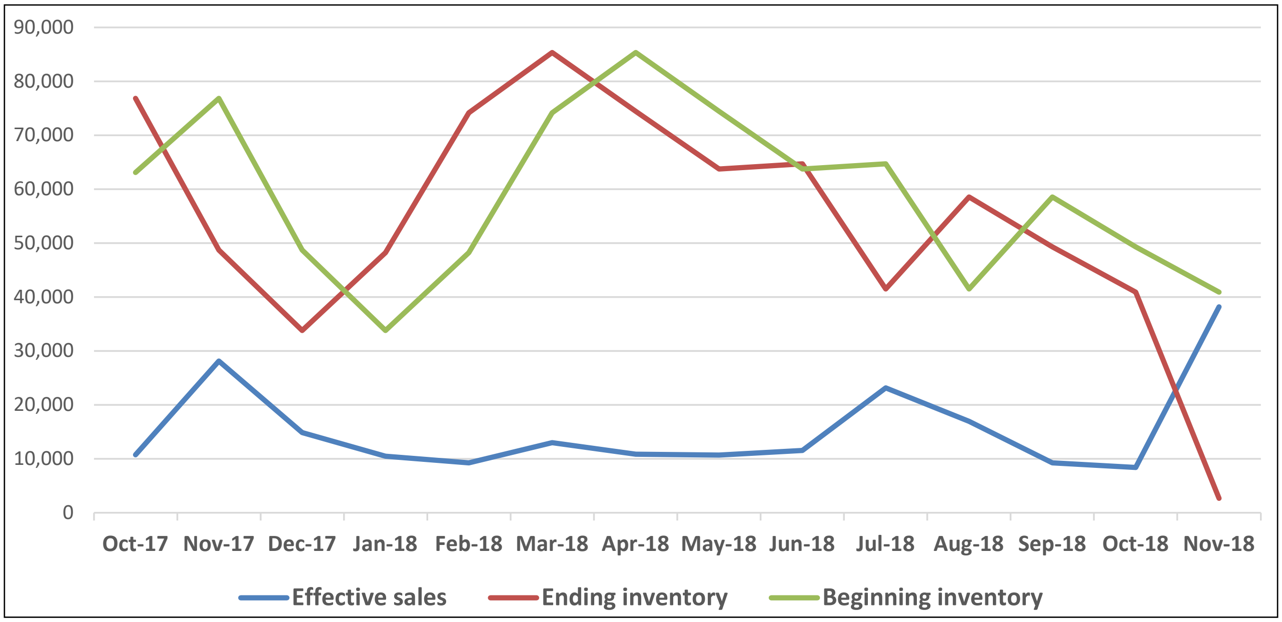

Figure 7. Push system inventories and sales — fragrance SKU.
Source: Developed by the authors.

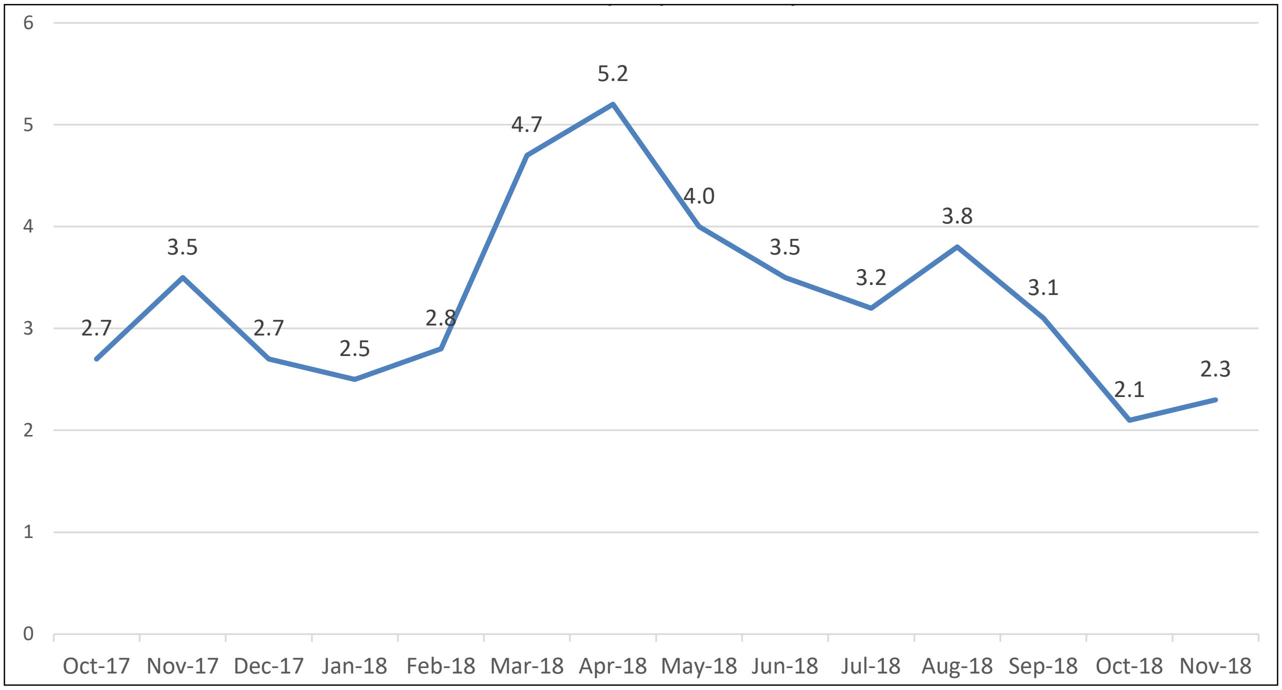

Figure 8. Cosmetics company's finished goods inventory coverage indicator — fragrance SKU.
Source: Developed by the authors.

The third-party manufacturer's average inputs inventory coverage, including ingredients and components, was 2.4 months, that is, average inventories from September 2017 to October 2018 elaborated as inventory months' coverage.

Proposed interventions: implementing the actions

One of the first phases that the intervention carried out was building awareness of the potential benefits that lean practices could provide to the chain's actors. To this end, a lean methodology training policy was established as preparation to implement the pull system. The training contents were delivered in several sessions involving tens of employees during the project's first 12 months.

To structure the awareness-building initiative, a consulting firm specializing in the lean methodology was retained to prepare a program intended to educate the cosmetics company's supply management and third-party manufacture management staff on lean tools, and provide the guidance and support needed to implement the pull system on their production chain. After a meeting to settle details with the consultants, a lean method training schedule was defined.

Senior management also designated a team of seven key project members, including the planning, manufacturing and third-party manufacturer relationship managers, the lean consultant, and the executive who was also a researcher.

Together with this team, an in-depth analysis was made of the primary causes of the problems found. Based on this, a set of countermeasures was developed to address the causes of the problems, and the team members developed a detailed intervention implementation schedule listing 15 main stages, as Figure 9, next, shows.

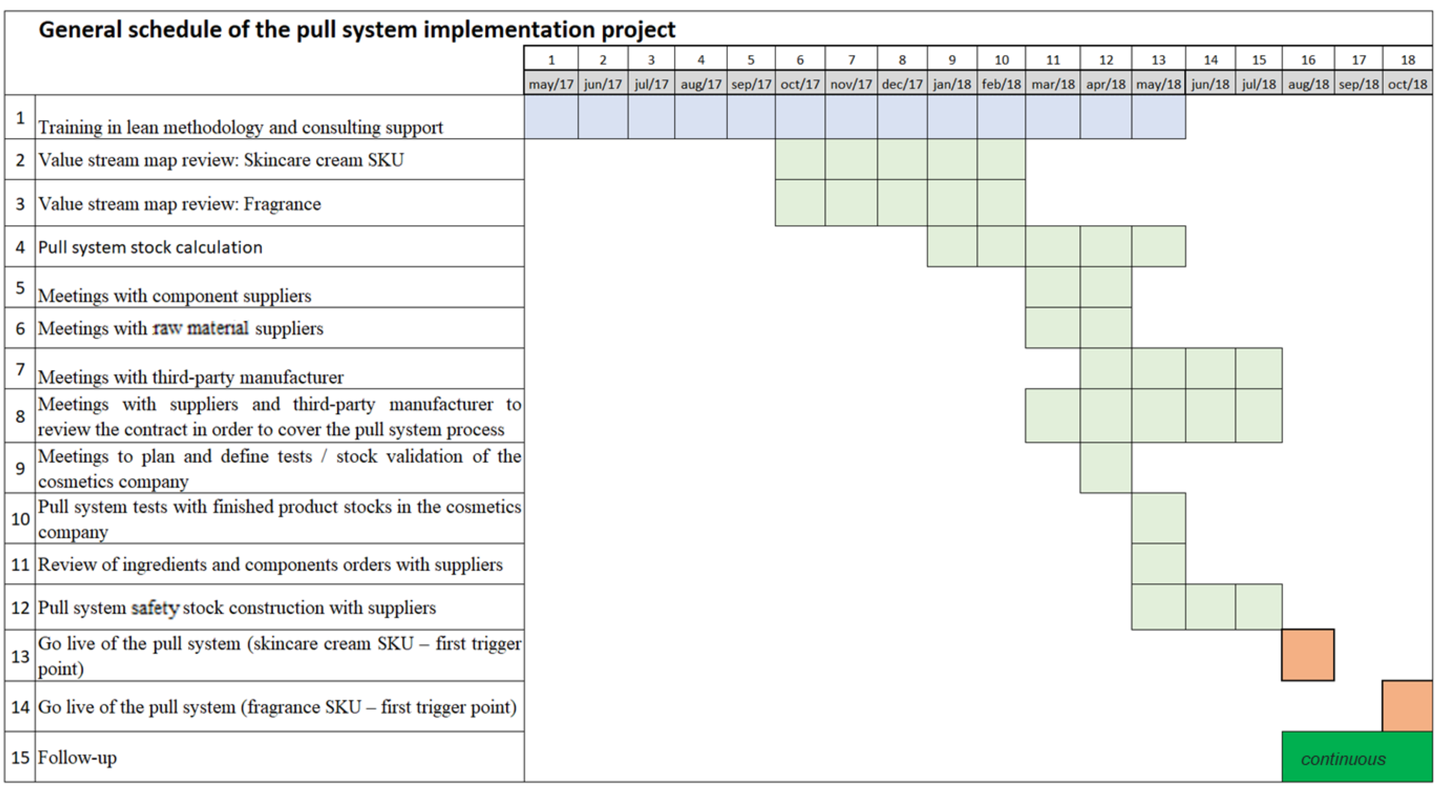

Figure 9. Pull system implementation schedule for the outsourced production chain.
Source: Developed by the authors.

This technical report lacks the space to provide a detailed discussion of each of the stages of the proposed schedule to enable the intervention. However, it is worth emphasizing that one of the intervention's most critical issues were reviews of the flows that built up the lead times (stages 2 and 3) and stock dimensioning (stage 4).

It was agreed at meetings between the cosmetics company and the third-party manufacturer that, under the new pull system, the cosmetics company would send firm product manufacture orders to the third-party manufacturer when the pull system's logic triggered a replenishment need through the resupply point, and the third-party manufacturer would endeavor to deliver the finished product within a maximum '42 calendar days' for fragrances and '55 calendar days for skincare products'.

At this stage of the intervention, the team designated by senior management held a series of meetings intended to survey the existing situation and forecast the intervention's future status. By definition, a current status map follows a product's path from order placement to delivery to determine the existing conditions. A future status map branches out from opportunities for improvement found by means of the current status map to reach a higher performance level at some point in the future (Womack, Jones, & Roos, 2007). Figure 10 shows a simplified version of such a map, going from a six-month to a 55-calendar day lead time in the case of skincare products.

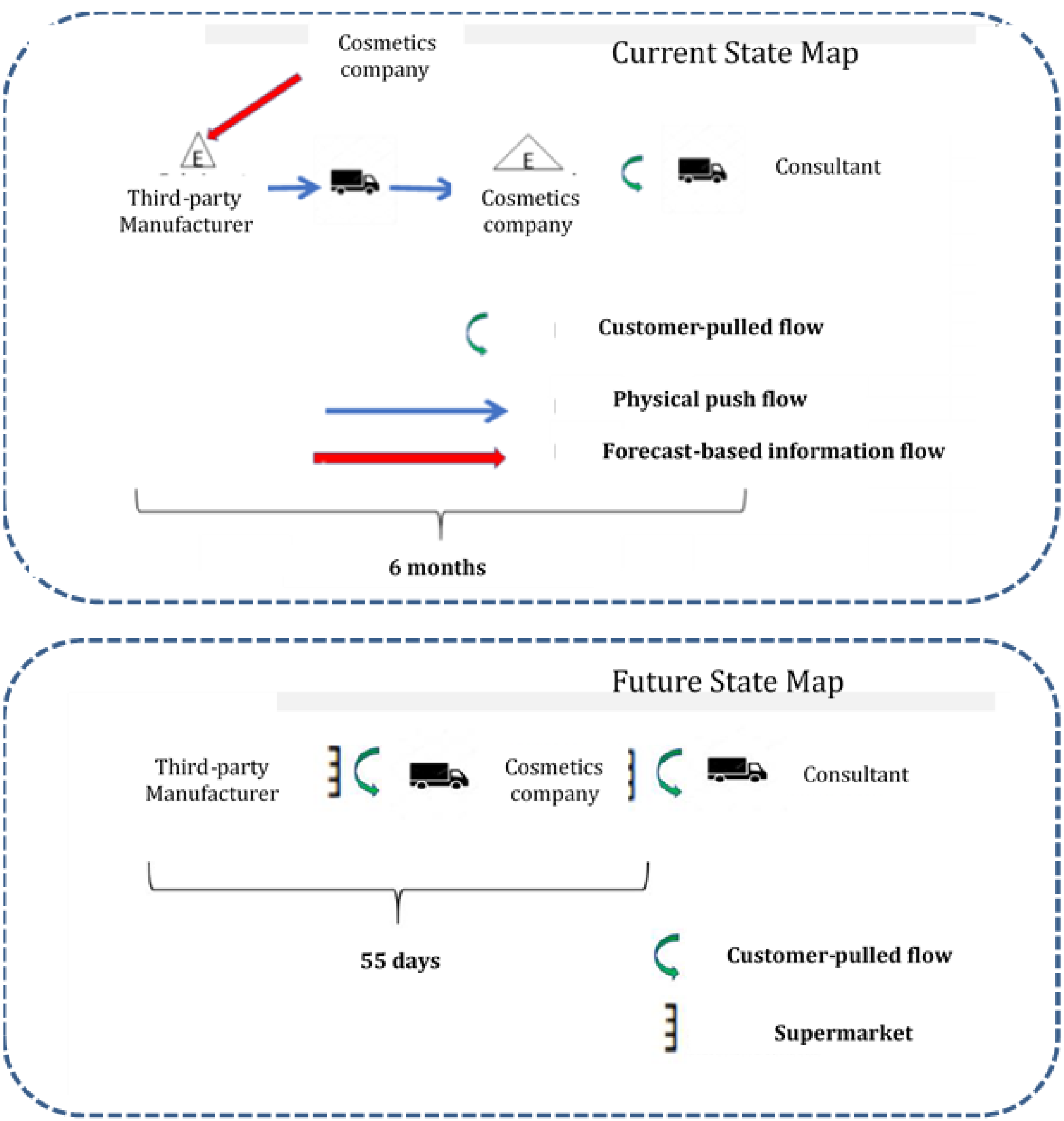

Figure 10. Current and future status map.
Source: Developed by the authors.

These lead times cover the entire cycle, including inputs acquisition, receipt and release times, as well as the time needed for programming, analysis, and release of the future product, until the effective delivery to the cosmetics company. Times were meticulously studied during the intervention by means of specific meetings with the workers involved in the intervention at both the third-party manufacturer and the cosmetics company. These workers prepared detailed maps and flow reviews to determine times.

Figure 11 illustrates one of the documents prepared at the flows and lead times redefinition meetings between the third-party manufacturer and the cosmetics company.

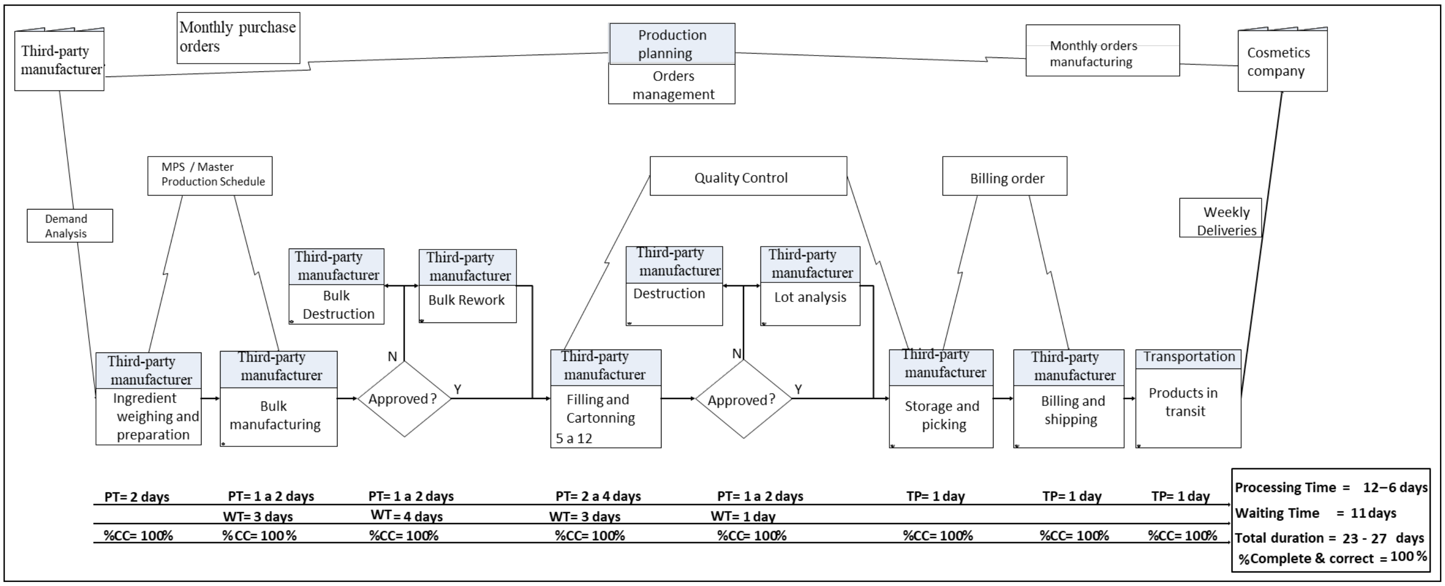

Figure 11. Illustrative flow and lead time redefinition by the intervention (stages 2 and 3).
Source: Developed by the authors.

As a key point of the intervention, it was agreed that the cosmetics company's new orders from the third-party manufacturer would be placed 'in accordance with consultants' sales', characterizing a pull system. To enable delivery within periods appropriate for the sales force, the chosen work mode embraced the lean manufacturing supermarket logic.

According to the supermarket logic, a prime condition applies so that each step in the immediately preceding process can only produce a good or product when the subsequent process or the end customer requests it, normally by means of Kanban systems. Kanbans therefore provide signals that trigger production orders, and may be used as visual cue cards, backlight panels, or even production orders between suppliers and customers (as in the intervention's case).

Dimensioning of the intervention's selected pull system then addressed the collective construction of a supermarket system made up of three parts: cycle stock, buffer stock, and safety stock for each SKU at hand, as Figure 12 shows.

For the proposed intervention, the cycle stock, which Figure 7 depicts in green, was the inventory needed to cover the entire item replenishment lead time, and translated as average daily demand for the item multiplied by the number of days needed to replenish the item, which was 55 days for the cream SKU and 42 days for the fragrance SKU.

As actual demand — through orders from consultants — consumes the cosmetics company's cycle stock, it decreases until reaching a level referred to as 'trigger point.' It was agreed with the suppliers that, upon reaching this point, a replenishment order would be fired off to the suppliers of the SKUs at hand. Similarly, the third-party manufacturer and the cosmetics company also agreed on the levels of the buffer stock and the safety stock.

Dimensioning of the real inventory levels applicable to the intervention involved calculating average monthly sales over 12 months to obtain a mean and a standard deviation for each item. In addition, these levels also considered the newly agreed lead times (55 and 44 days) and MOQs (minimum order quantity), which are the minimum batch runs that the third-party manufacturer requires.

Based on these parameters, the team dimensioned each of the inventories making up the pull system for the items at hand. To illustrate the supermarket logic, Figure 13 summarizes the quantities agreed between the third-party manufacturer and the cosmetics company for the project's two SKUs.

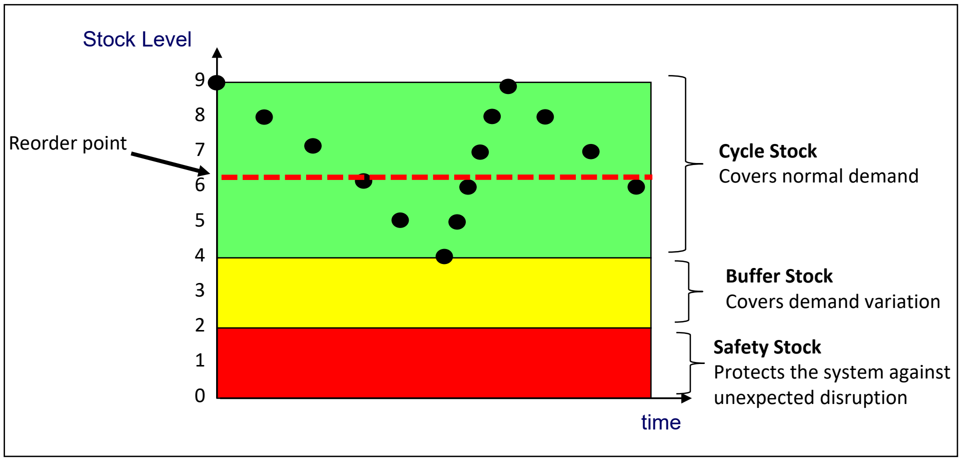

Figure 12. Supermarket system adopted for the intervention.
Source: Developed by the authors.

	SKU Skincare cream *Units*	SKU Fragrance *Units*
Cycle stock = demand within the lead time	150.000	25.000
Buffer stock = Stock planned to cover the demand variability in the period. In this case, 2 sigma were used	39.105	4.028
Safety stock = Defined to cover eventualities. In this case, 2 demand weeks were used. Total stock dimensioned for the pull system	40.555	7.783
Total pull system stock	229.660	36.811
Trigger point = Stock level that when reached, triggers a replacement order. It should cover the replacement lead time + safety stock + Buffer stock	228.361	26.339

Figure 13. Functional parameters of the intervention's pull logic.
Source: Developed by the authors.

Review of the intervention's outcome

After implementation of the pull system, the principal lead time and inventory indicators were collected anew in a period following the intervention, to determine the indicators' behavior and compare them with pre-intervention results. The following sections analyze the results.

Impacts on sales forecast accuracy results

As for sales forecasts, there was an important gain in accumulated accuracy under the pull logic, due to increased assertiveness in the smaller time frame. Table 4, next, shows the history of forecasting error measurement results for the two SKUs at hand.

Table 4. Demand forecasting error under the pull system.

SKU: Skincare Cream				
	Forecast Lag 6	Effective Sales	Absolute Error	% Error
Oct-18	74,404	67,284	7,120	9.6%
Nov-18	67,201	66,487	714	1.1%
Dec-18	60,266	56,338	3,928	6.5%
Jan-19	37,748	17,863	19,885	52.7%
Feb-19	39,241	16,348	22,893	58.3%
Mar-19	36,448	14,451	21,997	60.4%
Apr-19	25,001	12,987	12,014	48.1%
May-19	23,267	14,528	8,739	37.6%
Jun-19	23,993	14,599	9,394	39.2%
Jul-19	18,567	13,891	4,676	25.2%
Aug/19	14,916	14,209	707	4.7%
	421,051	**308,985**	**112,066**	**27%**
SKU: Fragrance				
	Forecast Lag 6	Effective Sales	Absolute Error	% Error
Dec-18	8,153	12,688	4,535	55.6%
Jan-19	8,829	5,526	3,303	37.4%
Feb-19	9,158	7,846	1,312	14.3%
Mar-19	9,673	8,252	1,421	14.7%
Apr-19	8,023	8,654	631	7.9%
May-19	11,228	11,243	15	0.1%
Jun-19	10,642	12,081	1,439	13.5%
Jul-19	34,414	19,426	14,988	43.6%
Aug-19	24,979	11,114	13,865	55.5%
	125,098	**96,830**	**41,509**	**33%**

Note. Source: prepared by the authors.

For the skincare cream SKU, mean error between demand forecast at ordering time and real effective sales was approximately 27% in the period from October 2018 to August 2019. Accumulated average percentage accuracy was approximately 73% in the same period.

Compared with the accumulated forecasting accuracy performance for the period at hand under the push logic, with 90% accumulated error and 10% accuracy, there was a significant gain in accuracy rates.

For the fragrance SKU, the mean error between forecast demand at ordering time and real effective sales was around 33% in the period from December 2018 to August 2019. Accumulated average percentage accuracy was approximately 67% in the same period.

Compared with the accumulated forecasting accuracy performance for the period at hand under the push logic, with 61% accumulated error and 39% accuracy, there was a significant gain in forecasting accuracy.

Impacts on process flow lead times

In terms of lead time, there was a significant reduction in results between the pull system and the previous push system. Table 5, next, shows the lead time history for the two SKUs at hand under the pull system logic.

Comparing the skincare cream SKU's lead times between the push and pull logic periods, there was a 62.5% reduction in the time as measured from order placement to delivery date. The time under the push system was 148.6 days, versus an average 51.8 days under the pull system. Lead time standard deviation dropped to 13.3 days, down 28% compared with the standard deviation under the push system, which was 18.5 days.

Comparing the fragrance SKU's lead times between the push and pull logic periods, there was a 66.7% reduction in average time as measured from order placement to delivery date. The time under the push system was 147.8 days, versus an average 49.3 days under the pull system. Lead time standard deviation dropped to 9.0 days, down 58% compared with the standard deviation under the push system, which was 21.6 days.

Table 5. Post-intervention pull system lead times.

	Skincare Cream	
Order Date	Date of 1st Delivery	Lead-time (calendar days)
08/30/18	10/08/18	39
09/27/18	11/23/18	57
11/22/18	01/04/19	43
01/10/19	03/19/19	68
	Average:	51.8
	Standard deviation:	13.3
	Fragrance	
Order Date	Date of 1st Delivery	Lead-time (calendar days)
10/26/18	12/05/18	40
12/19/18	02/18/19	61
03/08/19	04/22/19	45
06/24/19	08/14/19	51
	Average:	49.3
	Standard deviation:	9.0

Note. Developed by the authors.

Impacts on inventory levels

As for inventories, there was also a change in the behavior of inventory coverage indicators relative to demand.

In the pull system scenario, the cosmetics company's finished goods inventory level was closer to the level of demand, reducing the previous system's mismatch.

Figure 14, next, shows this behavior in the case of the skincare cream SKU.

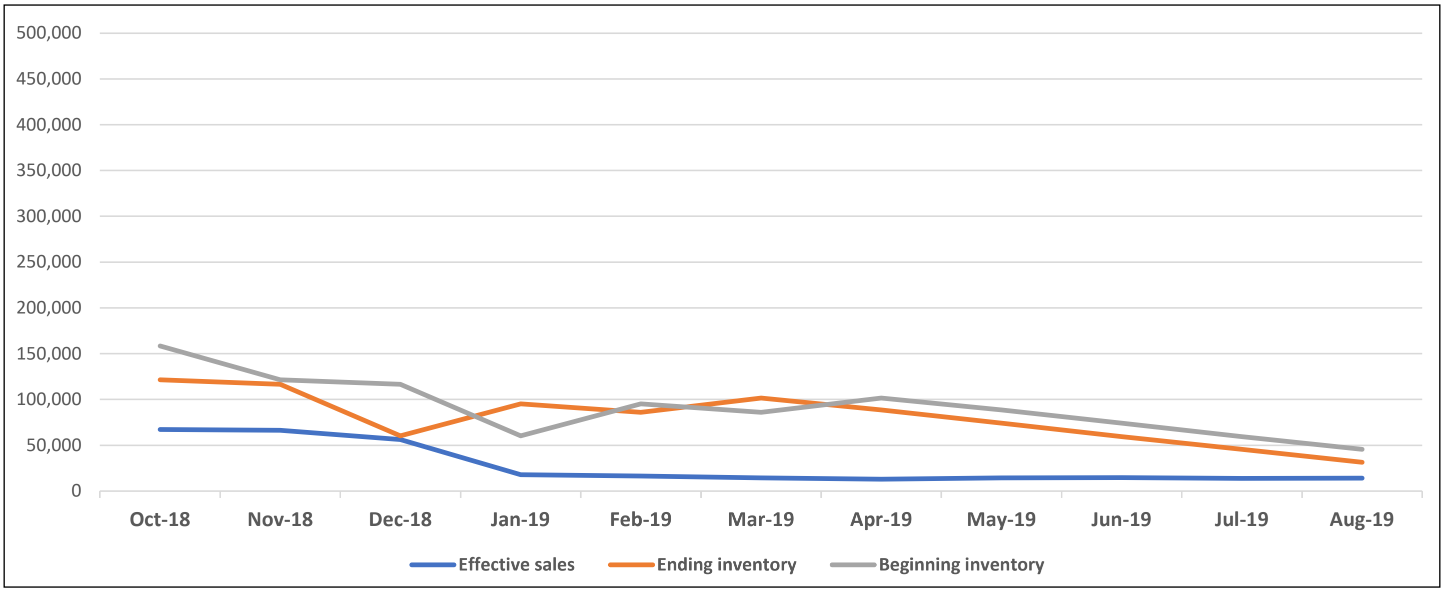

Figure 14. Pull system inventories and sales — skincare cream SKU.
Source: Developed by the authors.

In the period under the pull logic, the skincare cream SKU's average start-of-month inventory was reduced to 91,595 units, whereas average monthly sales volume dropped to 28,090 units. As a result, the ratio of average start-of-month inventory to average monthly sales volume was 3.3. Comparing this result with that under the push system, where the ratio between the two indicators was 3.8, the study finds a 15% decrease in the ratio between average start-of-month inventory and average monthly demand.

Similarly, the study observed the average end-of-month inventory of the skincare cream SKU under the pull system, which was 80,038 units. Calculating the ratio of this result to average monthly sales volume of 28,090 units yields 2.8 months.

Comparing this result under the pull system with that obtained under the push system, where the ratio between the two indicators was 3.5, the study finds an 18% decrease in the ratio between the average end-of-month inventory coverage level and average monthly demand.

The finished goods inventory coverage graph under the pull system for the skincare cream SKU indicates an average coverage of 2.7 months' sales. This corresponds to a 32.5% decrease in the months' coverage indicator compared with the same indicator under the push system, as Figure 15, next, shows.

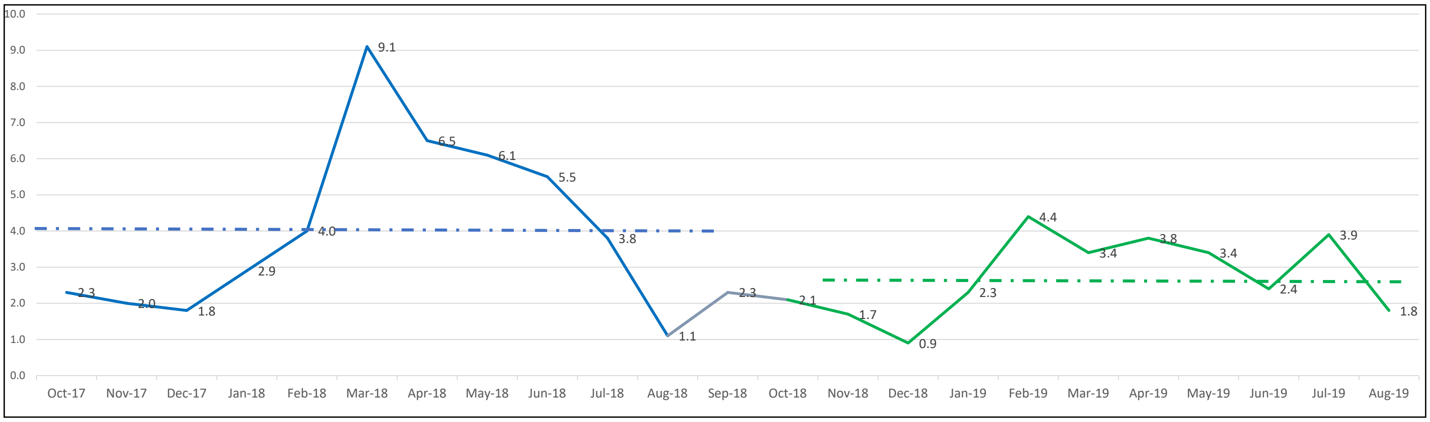

Figure 15. Inventory coverage variation — skincare cream SKU.
Push system (blue) versus Pull system (green). Source: Developed by the authors.

In terms of overall inputs inventories, including ingredients and components, average coverage was 3.51 months under the pull system. This represents a small 1% decrease compared with the same indicator during the evaluation period under the push logic, which was 3.52 months' inventories, indicating no significant change in the third-party manufacturer's inputs inventory.

For the fragrance SKU's inventories, a similar change was seen in the behavior of inventory coverage indicators relative to demand, as the cosmetics company's finished products inventory level drew closer to demand levels, reducing the mismatch present under the push system.

Figure 16 shows the fragrance SKU's behavior.

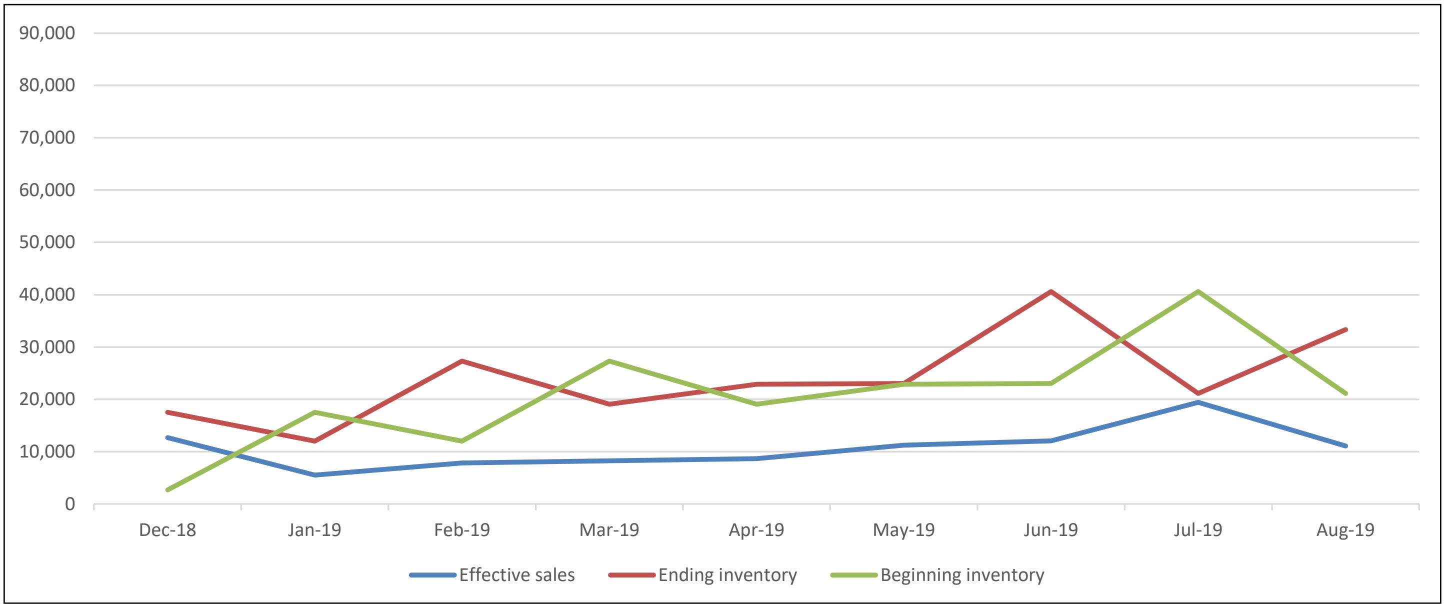

Figure 16. Pull system inventories and sales — fragrance SKU.
Source: Developed by the authors.

In the period under the pull logic, the fragrance SKU's average start-of-month inventory was reduced to 20,700 units, whereas average monthly sales volume was 10,759 units. As a result, the ratio of average start-of-month inventory to average monthly sales was 1.9. Comparing this result with that under the push system, where the ratio between the two indicators was 3.8, the study finds a 50% decrease in the ratio between average start-of-month inventory and average monthly demand.

As for the fragrance item's end-of-month inventories, the study found 24,103 units in the period under the pull system. Calculating the ratio of this result to average monthly sales volume of 10,759 units yields 2.2 months.

Comparing this result under the pull system with that under the push system, where the ratio between the two indicators was 3.5, the study finds a 37% decrease in the ratio between end-of-month inventory levels and average monthly demand.

The finished goods inventory coverage indicator for the fragrance SKU shows an average 2.1 months' coverage in the period under the pull logic. This average coverage level corresponds to a 36% decrease from the same indicator under the push logic, which was 3.3 months, as Figure 17, next, shows.

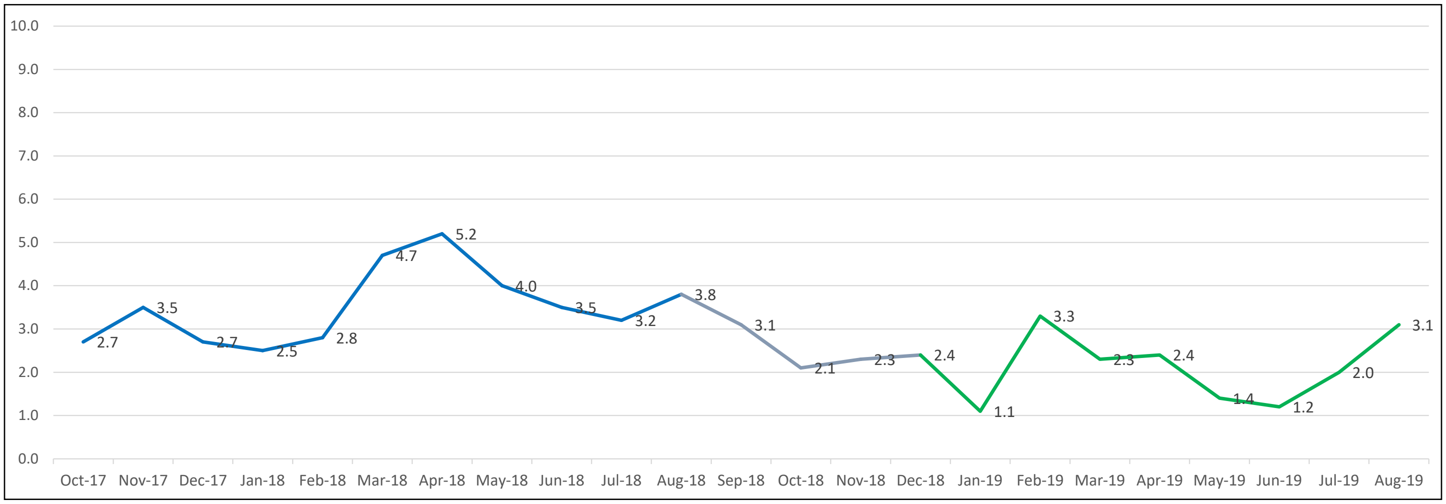

Figure 17. Inventory coverage variation — fragrance SKU.
Push system (blue) versus Pull system (green). Source: Developed by the authors.

In terms of overall input inventories, including ingredients and components, average coverage was 1.8 months under the pull system. This represents a significant 14% decrease compared with the same indicator during the evaluation period under the push logic, which was 2.5 months' inventories, indicating a material reduction in the third-party manufacturer's inputs inventory.

TECHNOLOGICAL CONTRIBUTIONS

As a contribution to the knowledge base in the operations area, it is worth pointing out that this intervention enabled the authors to suggest a roadmap for the implementation of the pull system based on the action research project's experience. Figure 18, next, describes the roadmap.

***ROADMAP* - PULL SYSTEMS IMPLEMENTATION**

PHASE	**1. Lean methodology training**	**2. Analysis unit definitions - SKU ingredients and components**	**3. Current state value stream map**	**4. Future state value stream map**	**5. Lead times breakdown**	**6. Pull system calculation**	**7. A3 elaboration**
TOOLS	*Value stream mapping* *Kaizen* *A3* *Gemba walk* *Pull system*	SKU composition analysis	*Value stream mapping* *Kaizen*	Value stream mapping *Kaizen*	*Value stream mapping*	*Pull system*	*A3*
PHASE	**8. Contract supply chain reviews**	**9. Data collection - push system**	**10. Vallidation of the pull system calculation**	**11. *Pull system go live***	**12. Data collection - Pull system**	**13. Compative analysis of main KPIs**	**14. Qualitative assessment with interviews and lessons learned analysis**
TOOLS	*commercial additives*	*analysis of hostorical data in the push system*	*Pull system test segregating excess inventory of push system*		*Analysis of hostorical data in the pull system*	*Comparative analysis between data from pull systems*	*Interviews* with key project stakeholders

LEAN MANAGEMENT SYSTEM: Leadership total support - Trainning - Communication - Results

Figure 18. Pull system implementation roadmap.
Source: Developed by the authors.

According to the roadmap, the stages are numbered to suggest an implementation sequence for a production system change from push to pull.

It begins by building the skills of the actors who will play a role in the intervention, who must be trained in the main lean tools to be used. The intervention analysis units are then defined, detailing the SKUs and the respective inputs for evaluation.

Following that, the current and future states of the system on which the intervention will be implemented are mapped, identifying all points for improvement and changes needed to reach the future state. The future state design activity comprehends the lead time breakdown task, which provides details on each activity's time, and the pull system dimensioning exercise.

All of these preparatory stages are formalized in document A3, which seals the team's commitment to the plan's execution.

The following stages, the terms and conditions of supply and agreements with the main suppliers involved must be reviewed, underscoring new operation dynamics and the responsibilities of each firm involved in the new context. At the same time, historic data are collected on the push system in force before the intervention.

The trial and validation stage for the new pull production system before it goes live enables validating the previously defined times in a real business environment, using the push system's surplus inventory as a safety net in the event of failure during trials.

After the pull system goes live, monitoring it by means of continuous data collection enables controlling its functioning and evaluating its impacts on the production system's main indicators. A qualitative assessment based on interviews with the main actors involved adds to the understanding of the intervention's effects, as it captures certain aspects that mere indicator reading and interpretation often fails to reveal.

Another important contribution from this study is the need to assess the tradeoff of the effort of manually managing plans for the SKUs whose production logic is changed from push to pull in addition to the planning routines for the other SKUs, which remain under the push system.

The countless benefits that the intervention provides include one that concerns reduced additional planning work by means of the elimination of rework present under the push system in connection with adjustments, corrections, increments, cancellations, or postponements of orders already placed. The study found that the rework reduction exceeds the additional manual control effort under the pull system. Furthermore, the suggested adaptation of the ERP to incorporate the controls and reduce manual efforts further increases the benefits of the pull system in this tradeoff.

Another important tradeoff to consider concerns the commercial and contractual challenges facing the promotion of the changes with manufacturers and suppliers versus operational gains from the intervention. The main difficulties found involved the manufacturers' and suppliers' concern over the need to disclose detailed manufacturing process data and information, as well as fears that the system might somehow affect their contracts' profitability.

It became clear that a pledge to not harm any of the firms involved as a result of implementation of the pull system, a pledge to cover the costs of input inventories not absorbed by the new system after a certain period, and the rapid results obtained under the pull system, with more stable production programming, enabled reducing commercial and contractual roadblocks and insecurity with manufacturers and suppliers, leading them to more quickly overcome these issues and doubts as orders under the pull system were executed, benefits were revealed, and fears were dispelled.

CONCLUSIONS

As concerns its core purpose, this action research project enables evaluating the effects of an intervention in the production system of a dyad made up of a cosmetics company and its third-party manufacturer. Analysis of inventory coverage and lead time indicator readings showed important variations in the indicators' behavior under the two production logics.

The intervention did in fact improve the selected indicators. Table 6 summarizes the main indicators in the pre- and post-intervention periods.

Table 6. Summary of the research project's results.

	Before intervention		After intervention			
	Push system		Pull system			
Average sales forecast error (% avg error)	SKU Skincare Cream	SKU Fragrance	SKU Skincare Cream	70% reduction	SKU Fragrance	46% reduction
	90%	61%	27%		33%	
Average lead time (calendar days)	SKU Skincare Cream	SKU Fragrance	SKU Skincare Cream	65% reduction	SKU Fragrance	67% reduction
	148.6	147.8	51.8		49.3	
Average finished goods inventory level of the Cosmetics company (months of stock)	SKU Skincare Cream	SKU Fragrance	SKU Skincare Cream	32% reduction	SKU Fragrance	36% reduction
	4.0	3.3	2.7		2.1	
Average ingredients and components inventory level of the third-party manufacturer (months of stock)	SKU Skincare Cream	SKU Fragrance	SKU Skincare Cream	stable	SKU Fragrance	24% reduction
	3.52	2.5	3.51		1.8	

Note. Prepared by the authors.

Concerning the behavior of order lead times after the intervention, there was a significant reduction for both of the SKUs at hand, the reduction being greater than 60% compared with lead times under the push logic. The skincare cream SKU's reduction was 65.2%, whereas the fragrance SKU's was 66.7%.

Another important observation concerning lead times is that not only they were sharply decreased, but so did lead time variability. The standard deviation of the skincare cream SKU's lead time was down 28%, whereas the decrease for the fragrance SKU was 58%. This may suggest that lead time variation decreased with the decrease of the lead times themselves.

The same behavior was also seen in connection with sales forecasting assertiveness. Given the smaller intervals that the pull logic enables, the study found that the sales forecasting error between order placement and delivery of the products was reduced from 90% to 27% in the case of the skincare cream SKU and from 61% to 33% for the fragrance SKU.

One expectation arising from these results is a potential positive impact in inventory management, as observed in this intervention, where the behavior mismatch between inventory curves and demand levels seen under the push system clearly shifted to a different behavior pattern, where the inventory curves drew much closer to the respective sales levels, enabling a reduced inventory coverage.

Analyzing average end-of-month inventories, the reduction under the pull system was 18% for the skincare cream SKU and 37% for the fragrance SKU, confirming that the inventory coverage level decreased relative to the sales level.

Although both cases showed reduced finished products inventory coverage, the study found that the fragrance SKU's reduction was greater. It became evident that the benefits from the pull system were smaller for the skincare cream SKU because of the gradual demand decrease in the pull system period as a result of discontinuation arising from an SKU version change, leading to conclude that SKU portfolio stability is a critical factor that must be taken into account when implementing the pull system, as dimensioning relies on historic data as well as demand forecasts to define the system's parameters.

As for concerns over the possibility of a decrease in the cosmetics company's finished product inventories — as was the case — might lead to input inventories buildup at the third-party manufacturer, the intervention may have shown that there was no significant change in manufacturers' input inventory levels.

Even in the face of additional agility required from manufacturers because of the chain's shorter lead times under the pull logic, the study found that the overall level of input inventories under the pull system was stable for the skincare cream SKU, and there was even a decrease in input inventories for the fragrance SKU.

Notwithstanding the significant decrease in sales forecast errors, lead times, and SKU inventory levels, as Table 6 shows, the intervention can be said to have drastically changed production planning and programming as the cosmetics company abandoned the conventional ERP production planning system based on sales forecasts and embraced planning in line with actual inventory levels. The change in logic from push to pull and the developments thereof were clearly the main change that this technological report aimed to show.

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