Introducing new RFID-enabled indicators to evaluate the performance of fashion retailers

Bertolini M.*, Maggiali L., Rizzi A.*, Romagnoli G.*, Volpi A.*

** Dipartimento di Ingegneria e Architettura – Università di Parma, Viale G.P. Usberti 181/A, 43124, Parma – Italy (giovanni.romagnoli@unipr.it)*

Abstract: The criticality of Out Of Stock (OOS) situations has long been acknowledged in the fashion and apparel sector, where, due to short lifecycles of products and high unpredictability of customers' demand, OOS often become lost sales and reduced revenues. Although the sales floor areas of mass retailers are constantly monitored by salespersons that visually control the OOS or near-OOS Stock Keeping Units (SKUs), and replenish them accordingly, OOS still causes disappointed customers and lost sales. Radio-Frequency Identification (RFID) has proven to be a very successful technology in decreasing OOS, particularly at store and shelf level, and the concept of OOS was often related to sales velocity, i.e. the number of items sold per day at a given granularity level (e.g. SKU, model, class). In this paper, we introduce a new category of Value-Added Indicators, that also considers (i) the average number of items displayed on the sales floor area at a given granularity level, and (ii) the average time that items, at a given granularity level, spend on the sales floor area before sale. These new indicators can be used to understand how quickly items sell, and thus to avoid OOS situations, but also to support the assortment and replenishment process, and thus to maximise the profit achievable for a given space available in the sales floor area. These indicators were implemented and calculated in a store of a major fashion retailer, to assess their advantages and disadvantages from a practical point of view.

Keywords: RFID; Value-Added Indicators; Metrics; Fashion and apparel sector; Out Of Stock

1. Introduction

The situation of Out of Stock (OOS) is a major problem in supply chain management, as it affects all actors of a supply chain, from end customers to suppliers (Gruen & Corsten 2007). OOS can be defined as 'a product not found in the desired form, flavour or size, not found in saleable condition, or not shelved in the expected location' (ECR Europe 2003). According to Aastrup & Kotzab (2010), consumers can answer in several different ways to OOS, and an important stream of research in OOS has developed several decision trees or decision typologies to understand consumer responses. Zinn & Liu (2001, 2008) summarised all this stream of research under the SDL acronym, meaning Substitute, either within the same brand or with another brand, Delay, or Leave, subdivided into buy at another store and do not purchase the item (Aastrup & Kotzab 2010).

Although the customer responses vary widely, all researchers agree that OOS has a significant impact on sales, which may even exceed the value of lost sale. This possible consequence is due to the considerable insights that indicate great consumer dissatisfaction when facing OOS situations. In their 2003 study, Corsten & Gruen (2003) pointed out two main causes for OOS events worldwide, that are errors in (i) forecasting consumers' demand and in (ii) shelf-replenishment. Although the same authors also suggested different causes for OOS situations (e.g. distribution centres or manufacturers), the above-mentioned causes are much more frequent. Also, Corsten & Gruen (2003) evaluated the consequences of OOS events in terms of lost sales, with a worldwide benchmark of 3.9% in the fast-moving consumer goods, and significantly varying averages across different categories of products.

In the last decade, Auto-ID technologies, and especially Radio-Frequency Identification (RFID), have emerged as leading solutions to reduce OOS. Just 10 years ago, Gruen & Corsten (2007) considered the potential of RFID to address shelf OOS, although 'due to technological and financial reasons, most … RFID applications [had] been limited to tags on pallets and cases and [had] not descended to the individual item level'. Only a few years later, researchers started to demonstrate that RFID was very effective in improving inventory management, reducing OOS, improving inventory accuracy, and enabling omnichannel retailing (Hardgrave 2012; Hardgrave et al. 2011; Bertolini et al. 2015).

In particular, in a study carried out at Wal-Mart stores, Hardgrave, Waller, & Miller (2006) investigated the correlation between the impact of RFID in reducing OOS and the sales velocity of different items. Sales velocity can be defined as the number of units of product that are sold per day, at a given level of aggregation, such as stock keeping unit (SKU) or model. The study concluded that RFID effect in reducing OOS varies by the units sold per day; this was also verified by controlling other variables, such as pack size and shelf quantity.

However, the wider diffusion of RFID technology at item level has now made it available to control other important variables, such as shelf quantity and 'exposure time', that is the amount of time that an item is available for customers' purchases on the sales floor area. In the present paper, we propose two new RFID-enabled indicators, that consider shelf quantity and exposure time, to investigate how RFID can be used to improve inventory management and, eventually, increase sales. The indicators that we propose have been deployed in a store of a fashion and apparel retailer, namely Diffusione Tessile; the store is located in Central Italy.

2. An overview of the literature focused on RFID and OOS

2.1 Pallet- or case-level tagging

In recent years, a constantly growing number of studies has been focusing on the effectiveness of RFID technology in reducing OOS conditions. To achieve this goal, RFID tags were firstly applied at tertiary or secondary packaging (i.e. pallet- or case-level tagging). Most of the studies that investigate the impact on OOS of RFID tags applied at pallet- or case-level were performed in the fast-moving consumer goods retail, and so we will firstly refer to this sector. In a leading study, Hardgrave, Waller, & Miller (2005) asked the question 'Does RFID reduce out of stock'? The results provided by that study suggested that, from several different points of view, RFID was really making a difference. In their 2007 study, Riemenschneider et al. (2007) proved that one of the main business values of RFID was reducing OOS in retail. Just a few years later, Hardgrave et al. (2011) demonstrated that the effectiveness of RFID case-level tagging is not homogenous in reducing OOS across different product categories in the FMCG. Also, Bertolini, Ferretti, Vignali, & Volpi (2013) deployed an RFID pilot project in the supply chain of FMCG, with tags attached at case level. During the 4 months of the project, RFID allowed to optimise shelf stock, meaning that the pilot retailer was able of reducing at the same time OOS, capital holding costs, and shrinkage due to expired shelf life, by means of an efficient management of RFID data. This optimisation could generate potential savings accounting for as much as 1.7% increase of sale turnover.

However, we must note that the effectiveness of RFID in reducing OOS has become a particularly hot topic with the increasing deployment of RFID tags at item-level, and particularly in the fashion and apparel supply chain. This is mostly due to the following factors: (i) item-level tagging allows to track and trace items from when the tag is applied, which might be on end products, or even on raw materials (if they are tagged), up to the point of sale, and even beyond; (ii) the higher marginality of the fashion and apparel sector makes it less important to control the price of tags to ensure return on investments of RFID technology (Rizzi et al. 2016); (iii) the great progress in information and communication technology makes available both tools and knowledge to manage the massive amount of data that can be generated by item-level tagging.

2.1 Item-level tagging

In his 2010 numerical study, Gaukler (2010) simulates the operations of a retail store provided with stocks both in the backroom and in the sales floor. In these conditions, the author emphasises that RFID item-level tagging has a two-fold impact: first, it is very effective to improve backroom-to-shelf replenishment operations, and this results in an increasing number of products sold. Second, more products sold implies higher demand forecast and, thus, higher stock levels in the backroom. Furthermore, Gaukler (2010) suggests that the higher RFID benefits are related to the backroom-to-shelf replenishment process, with minor benefits due to an improvement of backroom stockings. Bertolini, Bottani, Ferretti, Rizzi, & Volpi (2012) showed that RFID-enabled inventory control has helped the supply chain of a major Italian fashion brand in decreasing OOS situations, thus resulting in higher turnover. In particular, the availability of real-time information of models available in the backroom caused an increase in turnover of about 0.8%, whereas the possibility of optimizing the replenishment process on the basis of real-time information about inventory and sales data could further increase sales turnover (between 4.9 - 11.1%).

Always considering the fashion and apparel supply chain, Bertolini et al. (2015) assessed that RFID technology for inventory count operations is more reliable than barcodes. Also, under different circumstances, the authors showed that RFID is more effective in detecting OOS situations than both barcode technology and the inventory data retrieved from the company's information system. In the same sector, a recent study of Bottani, Montanari, & Romagnoli (2016) demonstrated the capability of RFID to improve the shelf replenishment operations, and therefore reduce OOS situations and increase sales turnover. The study used a pilot project into an Italian fashion store and generated, by means of RFID data, a daily a list of models that were not available on shelves, although they were available in the backroom. These data triggered more precise backroom-to-shelf replenishment operations, which resulted in an increase in sales between 4.7% and 9.2%.

Another important topic that was already examined by Hardgrave et al. (2006) is which factors can influence or determine the effect of RFID on OOS. The authors demonstrate that sales velocity greatly influences the effect of RFID on OOS. The decrease of OOS caused by RFID varies by different velocities of sale of different items. This conclusions were also extended by Hardgrave, Aloysius, & Goyal (2013), which investigated the effectiveness of RFID in reducing the inventory record inaccuracy at different retail stores in two different field experiments. The study considered the effect of RFID-enabled visibility on different known predictors of inventory inaccuracy, such as (i) sales velocity, (ii) item cost, (iii) sales volume (i.e. sales velocity x item cost), (iv) variety (i.e. number of unique SKUs carried out in a store), (v) processing of RFID data and (vi) product category.

However, despite all of these studies on the factors that may influence the effect of RFID data on OOS, two important aspects where not yet taken into account. The datum of sales velocity, in fact, can be measured by means of point of sale (POS) data. As indicated in Bertolini, Romagnoli, & Weinhard (2016), RFID item-level tagging allows not only to monitor sales velocity, but also: (i) inventory level in real-time and (ii) the actual time spent on the sales floor per items at any level of aggregation (e.g. SKU, model, class). We make use of this additional information available from an even more data-rich industry to develop the new value-added indicators (VAIs) that are proposed in this paper.

3. The proposed indicators

As reported in the previous section, sales velocity measures only the number of items that are sold per every interval of time (e.g. per day), at a given granularity level. The first indicator that we propose is Shelf Utilisation Efficiency (SUE), and it considers the number of items sold, and the level of inventory available in the sales floor area (see green area in Figure 1). Finally, the Sales per Exposure Time (SpET) considers both sales and inventory level, as well as the exposure time (yellow area in Figure 1). We define exposure time as the time that items at a given aggregation level spend on the sales floor (and not in the backroom). The levels of aggregation considered in our test store start from read events at single EPC-level (Electronic Product Code), and they can be organised as in Figure 2.

As we have reported, sales velocity has been correlated in the literature to the incidence of OOS: by analysing the velocity by which items are sold, it is possible to divide them into categories and, therefore, support specific backroom-to-shelf replenishment processes. However, we suggest that sales velocity is not the only indicator to be considered, as inventory level and exposure time are also important to monitor items' performance, and thus avoid shelf OOS and, eventually, increase sales. These VAIs were specifically developed for the fashion and apparel sector, and tested with real data from a case store. The rationale behind our VAIs is that by monitoring not only sales velocities, but also SUE and SpET, that is inventory levels and exposure times, decision makers in fashion and apparel retail stores can be much more effective in reducing OOS and optimising store assortment (i.e. the number of items displayed per every model or class).

The calculation of our VAIs is possible by means of item-level tagged garments. In our test store, items are tagged from the distribution centre, and they are monitored by means of RFID readers at all the following processes: (i) shipping from the distribution centre, (ii) receiving at the store, (iii) replenishment in the sales floor area, (iv) inventory count (can be performed in the sales floor as well as in the backroom), (v) checkout or EAS gate. Note that processes also consider direction, such as item replenished in the sales floor and then maybe brought back to the backroom, and we refer to Bertolini et al. (2012) for a more detailed description of the RFID-enabled processes.

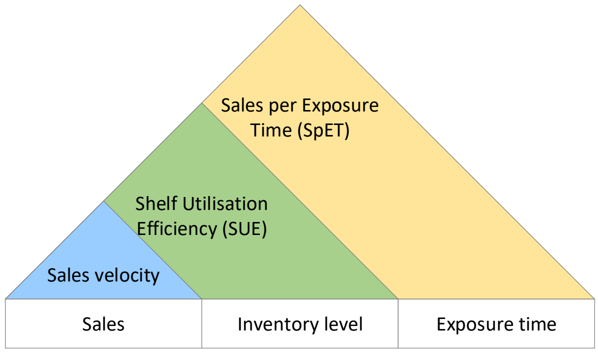

Figure 1: the concept behind the new indicators that we propose

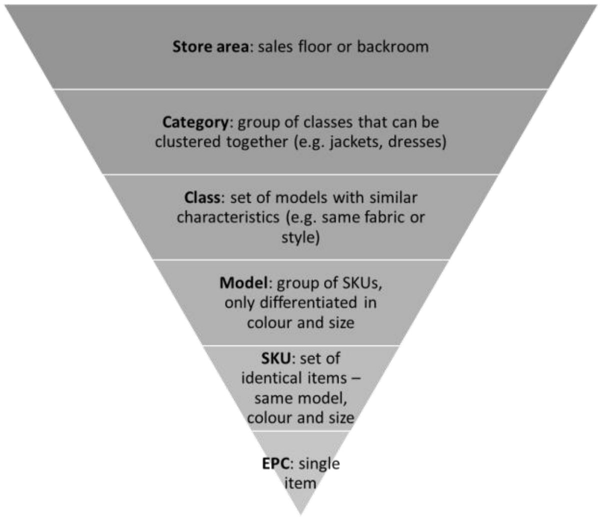

Figure 2: levels of aggregation considered at our test store

In detail, the proposed VAIs were calculated as in Eq. 1 and 2. Considering a generic *i-th* level of aggregation (e.g. category or class), we have:

$$SUE_i = \frac{sales\ velocity_i}{average\ sales\ floor\ inventory_i} \tag{1}$$

$$SpET_i = \frac{sales\ velocity_i}{total\ exposure\ time_i} \tag{2}$$

Firstly, we stress that each indicator may be calculated at any of the level of aggregation reported in Figure 2, and with any time unit. We suggest measuring time in days, and using categories, classes and models as reasonable and effective levels of aggregation, because they do not consider the effect of assorted sizes or colours. SUE_i divides the sales velocity$_i$ by the average inventory on the sales floor belonging to the *i-th* class/model. A simplified calculation of the average sales floor inventory$_i$ in a generic day *n* can be achieved dividing by 2 the sum of the inventory of item$_i$ at the store opening time of day *n* and *n + 1* (no operation on the sales floor inventory is performed overnight). Thus, SUE_i introduces a crucial factor to sales velocity of item$_i$: its (average) level of inventory.

Another key factor to be considered is the number of days that items of the *i-th* class/model spend on the sales floor, on average. This is exactly the goal of $SpET_i$, that divides the sales velocity$_i$ by the total exposure time$_i$, that is the sum of days that every *i-th* item spend on the sales floor. Note that the exposure time of every item$_i$ elapses the effective time that the item spends on the sales floor, without considering the time spent in the backroom, in case of returning items. Also, the total exposure time$_i$ sums up exposure times of every *i-th* garment, calculated at the EPC level; by doing this, both the average inventory$_i$ and the average exposure time$_i$ are considered.

4. A practical application of the proposed indicators

To better explain the calculation and suggest possible uses of the indicators that we propose, we report our case study in this section. Firstly, we selected a subset of classes, and the corresponding categories: upon request of both store and company managers, we selected the classes indicated in Table 1, due to their importance and criticality. The list of models belonging to each class is not reported, but only their number is indicated. As it can be seen from the table, the number of models per class varies widely, from 1 to several hundreds. On these classes, we calculated:

- Sales velocity$_i$ at different levels of aggregation: SKU, model, class and category.
- Sales floor inventory$_i$ at store opening at the same levels of aggregation. Average sales floor inventory$_i$ of a generic day n can be calculated as suggested in Section 3.
- We calculated Exposure time at EPC level, by measuring the time span between two different *bizlocations*, that are the logical locations constituted in which the information system positions the tag after a read event. Exposure time is achieved by summing (i) time sold - time sales floor and (ii) time backroom - time sales floor, considering when an item is sold or brought back into the backroom, respectively.
- Exposure times at EPC level were then aggregated at different granularity levels (SKU, model, class and category).

Table 1: categories and classes of the case study

Category	Class	Description	No. of models
Coats	1	Coat	12
	2	Overcoat + Raincoat	111
	3	Coat + 1 piece	2
	8	Short Coat	139
	48	Quilted Jacket	63
	49	Quilted Coat	1
Dresses	22	Dress	872
	32	Knitted Dress	76
	62	Jersey Dress	244
Jackets	34	Knitted Jacket	238
	36	Sweater	395
Pants	13	Long Pants	682
	18	Denim Pants	133
	78	Jersey Pants	70

Afterwards, we cleaned data by removing mistaken double reads (e.g. same items sold twice) and mistaken exposure times (e.g. items exposed for more than a season). The data cleaning process, however, affected less than 2% of around 300,000 read events. Figures 3 and 4 report both the VAIs, SUE and SpET, per class and category. SUE values are measured as percentage values (items sold per day / average daily inventory). SpET, instead, are measured as items sold per day / number of items x number of exposure days.

Coats have the greatest SUE (4.56%), with classes 1 and 48 having the greatest values (5.06% and 4.82%, respectively). Jackets, on the other hand, have lower SUEs (2.19%), with both classes 34 and 36 being the lowest performer (1.94% and 2.33%, respectively). Although all these categories sell every day between 2 and 5% of their average inventory, jackets need more than twice the average inventory of coats to achieve the same sales velocity. Quite different results can be achieved with SpET. According to this VAI, in fact, pants are the best performing category (0.025), followed by dresses and coats at almost equal SpET values (both 0.019). Jackets, again, have the lowest SpET value (0.007). A possible interpretation of SpET is that pants sell 1 item per day with an average total exposure time of 40 day x item (e.g. 40 items x 1 day on the sales floor, or 1 item x 40 days).

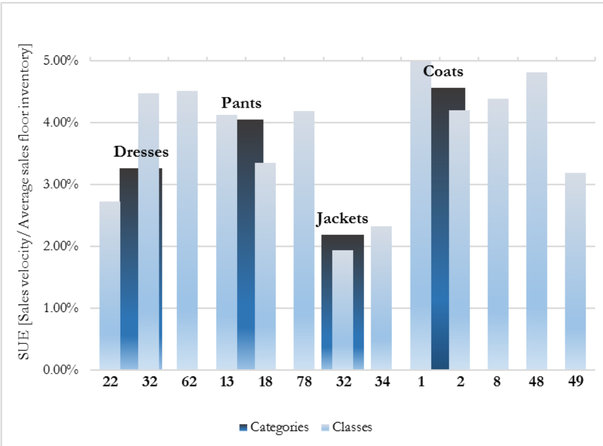

Figure 3: Shelf Utilisation Efficiency at category and class level

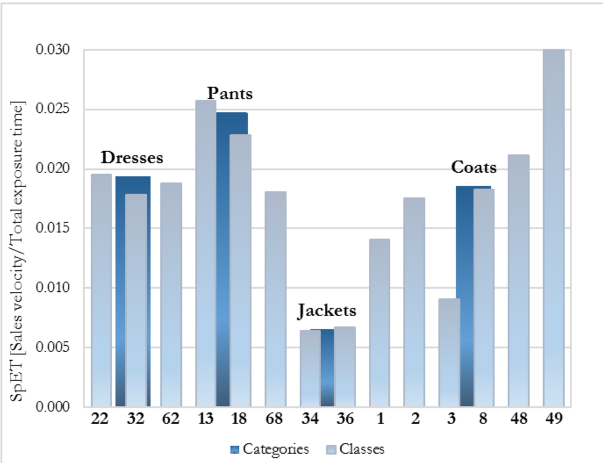

Figure 4: Sales per Exposure Time at category and class level

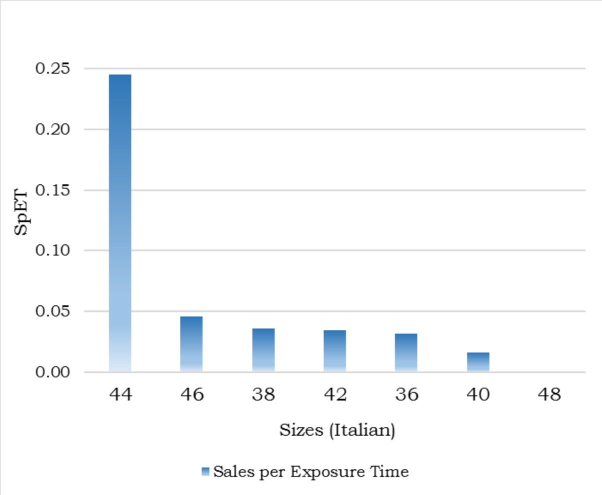

Figure 5: SpET for different sizes of a specific model (model Dattero - class 49)

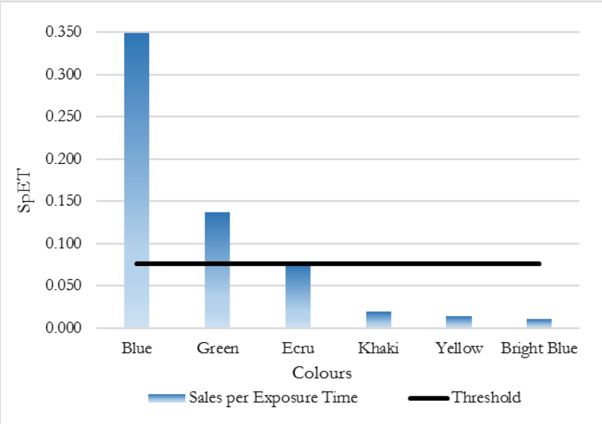

Figure 6: SpET for different colours of a specific model (model Dattero - class 49)

Figures 5 and 6 indicate how SpET could be used at model level, that is focusing on how different sizes or colours performs in terms of SpET. If we compare the values of Figures 5-6 with those of Figure 4, it is clear that we broke down the best performing class, according to SpET (i.e. class 49). This choice was done for three reasons: (i) we wanted to understand better the reasons behind the high SpET values of this class, (ii) we hoped to find significant differences between different colours and sizes on class 49 and (iii) this class only counts 1 model (i.e. Dattero), and thus analysing it is quite easy. As we will discuss in Section 5, we have also added a threshold value in Figure 6, located at 75% of the average SpET of model Dattero.

Finally, to better understand the relationships between sales velocity, SUE and SpET, we calculated the pairwise Pearson's correlation coefficients amongst these values. The results are reported in Table 2. Note that the table does not consider class 3, because this class counts only 2 models, and during the testing time of SUE none of these models was available on shelves. This reason also explains why class 3 is not visible in Figure 3. Note also that the pairwise correlations reported in the last row of Table 2 are calculated between their column and the one on the left (i.e. 0.36 is the correlation between SpET and SUE, and 0.05 the correlation between sales velocity and SpET).

Table 2: VAI values and pairwise correlations

Class	Sales velocity	SUE	SpET
1	0.37	0.051	0.014
2	4.97	0.042	0.018
8	38.01	0.044	0.018
13	1.63	0.041	0.026
18	8.12	0.034	0.023
22	3.58	0.027	0.020
32	5.12	0.045	0.018
34	8.58	0.019	0.006
36	0.22	0.023	0.007
48	5.08	0.048	0.021
49	8.31	0.032	0.030
62	0.06	0.045	0.019
78	38.00	0.042	0.018
Correlation	**0.05**	**0.14**	**0.36**

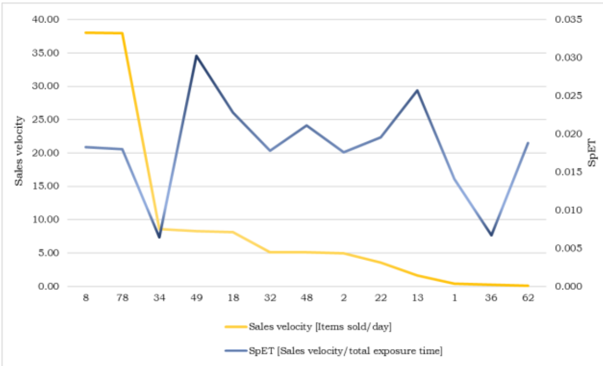

Figure 7: graphical comparison between sales velocity and SpET of different classes

Figure 7 also reports the graphical comparison between Sales velocity (in yellow) and SpET (in blue). It is clear from the figure that the two VAIs are not correlated (e.g. compare classes 13, 18, 49, and 62).

5. Discussion and conclusions

More than ten years ago, Hardgrave et al. (2006) demonstrated that sales velocity influences significantly the effect of RFID on OOS. Also, a later study by Hardgrave et al. (2013) extended the field of research by considering the effect of RFID on different predictors of inventory inaccuracy, and thus of OOS. In this paper, we exploited RFID technology to take into account average inventory levels and exposure times, and we proposed 2 new VAIs named Shelf Utilisation Efficiency (SUE) and Sales per Exposure Time (SpET). These VAIs were proposed analytically, and we also provided a case study from the fashion and apparel retail sector to demonstrate their applicability. We applied these indicators to a subset of categories and classes of products at a Diffusione Tessile store, located in Central Italy. The indicators were calculated at different levels of aggregation: category, class, and model, and they can be used with profit by decision makers at fashion and apparel stores. Firstly, we stress that these indicators are not absolute values, but they must be considered relatively.

We demonstrated that sales velocity is not correlated to SpET, and it shows only a weak correlation to SUE (0.14), as the common threshold value for indicating weak correlation is 0.1 (Field 2013). Thus, if compared to sales velocity, SUE and SpET provide different information. The first indicator (SUE) considers also the average sales floor inventory level, hence its name: shelf utilisation efficiency, whereas the second (SpET) takes into account total exposure time, that is the average sales floor inventory multiplied by the average time on the sales floor area. Although we did not provide quantitative results in this paper, from the qualitative point of view it is clear that SUE is a much more relevant indicator in preventing OOS. As an example, a model with 5% SUE will take, on average, 20 days to be completely OOS, against the expected 50 days to go OOS of a model with 2% SUE. Therefore, store associates can use SUE values to assess the risk of OOS for each category, class, and model. Furthermore, the possibility of having those indicators in real-time could be very effective in preventing OOS. We stress that the same information is not available from sales velocity values, because they do not consider average sales floor inventory.

SpET, on the other hand, shows a moderate correlation with SUE, and thus these VAIs provide different information, at least to some extent. These relationships are also visible from Table 2 and Figure 7, where we report graphical and numerical comparison of different indicators. SpET, for example, could be really beneficial for assorting and re-assorting sales floor areas. Quite often, in fact, fashion stores cannot display all the models that are available, due to (i) a limited space in the sales floor area and (ii) a high variety of different products, even within just one season. In these conditions, deciding which models to display, and which not, is a critical decision, that can result in mistakes, such as low-selling items exposed to the detriment of high-selling ones, and lost sales. Store managers, however, are often hindered from making well-informed decisions due to the availability of little information. Sales velocity is an important tool, but we believe that SpET can be much more useful to understand how quickly garments sell, also taking into account their average sales floor inventory and exposure time. For example, if a model has a relatively low SpET value, it means that its total exposure time (average inventory x average time on the sales floor) is bigger than its sales velocity. That is to say, the model can also sell very quickly, but it needs a lot of sales floor inventory and/or a long time on the sales floor to sell. On the contrary, a model with a (relatively) high SpET value is more effective in converting its total exposure time into sales.

For these reasons, store managers can use SUE and SpET data (Figures 3-4) to identify the best performing categories and classes, and thus allot more sales floor space to them. SUE considers how effective SKUs (or models, categories or classes) are in converting their sales floor inventory into sales: garments with high SUE values will sell, on average, higher percentages of their sales floor inventory every day. Furthermore, SpET considers also the total exposure time (i.e. total time on the sales floor area), and thus it evaluates how effectively and quickly garments on the sales floor can be converted into sales.

Similarly, Figures 5-6 show how different sizes or colours of the same model perform. We propose a threshold value, located for example at 75% of the average SpET of model 'Dattero' (see Figure 6), to suggest which colours may be exposed on the sales floor area (e.g. blue, green and ecru) and which may not (e.g. khaki, yellow, and bright blue). Also, Figure 6 may be used to suggest a possible 'replenishment kit', to be prepared beforehand and replenished together to maintain the same stock levels on the sales floor area (e.g. 1 ecru, 2 green and 5 blue, with sizes allocated according to Figure 5).

We note that the study is still not complete. The main limitations of our study can be summarised as follows:

- The new VAIs were proposed to the management of Diffusione Tessile for roll out, and the company has showed interest in the research, but it has not yet decided to fully implement them.
- In our case study, it was not possible to interrogate the RFID system to produce the sales price and/or the production costs of different garments. Providing SUE and SpET values with sales prices could tremendously help to increase their effectiveness and their use.
- Although SUE and SpET were proposed and calculated in our case study, the effects of those indicators on OOS and on sales turnover is still to be evaluated. We have not yet assessed from the quantitative point of view what impact SUE and SpET can have on OOS and store turnover.
- We still did not consider how stable the values of SUE and SpET are, and thus how robust can be the decisions made relying upon them.

The limitations of our study could be used as a basis for future research. Practitioners, for example, may implement the proposed VAIs in fashion and apparel companies (and not only in this sector, provided that necessary data can be calculated at the desired level of aggregation). Also, considering the sales price and/or production cost could greatly enhance the effectiveness of the proposed VAIs. Researchers, on the other hand, may investigate the last 2 bullet points, to understand the robustness of our VAIs and the quantitative effect of their implementation on OOS.

References

Aastrup, J. & Kotzab, H., 2010. Forty years of Out-of-Stock research – and shelves are still empty. The International Review of Retail, Distribution and Consumer Research, 20(1), pp.147–164. Available at:

http://www.tandfonline.com/doi/abs/10.1080/09593960903498284.

Bertolini, M. et al., 2012. Experimental evaluation of business impacts of RFID in apparel and retail supply chain. International Journal of RF Technologies: Research and Applications, 3(4), pp.257–282.

Bertolini, M. et al., 2013. Reducing out of stock, shrinkage and overstock through RFID in the fresh food supply chain: Evidence from an Italian retail pilot. International Journal of RF Technologies: Research and Applications, 4(2), pp.107–125.

Bertolini, M. et al., 2015. The impact of RFID technologies on inventory accuracy in the apparel retailing: Evidence from the field. International Journal of RF Technologies: Research and Applications, 6(4), pp.225–246.

Bertolini, M., Romagnoli, G. & Weinhard, A., 2016. Developing a new framework for Value Added Indicators enabled by RFID data in the fashion and apparel sector. In Proceedings of the Summer School Francesco Turco, Industrial Systems Engineering. Naples (Italy),13-15 September, pp. 182–186.

Bottani, E., Montanari, R. & Romagnoli, G., 2016. Improving sales turnover in fashion retailing by means of an RFID-based replenishment policy. International Journal of RF Technologies: Research and Applications, 7(1), pp.65–86.

Corsten, D. & Gruen, T., 2003. Desperately seeking shelf availability: an examination of the extent, the causes, and the efforts to address retail out-of-stocks. International Journal of Retail & Distribution Management, 31(12), pp.605–617.

ECR Europe, 2003. ECR – Optimal Shelf Availability, increasing shopper satisfaction at the moment of truth.

Field, A., 2013. Discovering statistics using IBM SPSS Statistics 4th Ed., London, UK: SAGE.

Gaukler, G.M., 2010. Preventing avoidable stockouts: the impact of item-level RFID in retail. Journal of Business & Industrial Marketing, 25(8), pp.572–581. Available at: http://www.scopus.com/inward/record.url?eid=2-s2.0-78049469007&partnerID=tZOtx3y1.

Gruen, T. & Corsten, D., 2007. A comprehensive guide to retail out-of-stock reduction in the fast-moving consumer goods industry,

Hardgrave, B.C., 2012. Omnichannel retailing - You can't do it without RFID. RFID Journal, p.1. Available at: http://www.rfidjournal.com/articles/view?10247 [Accessed July 18, 2014].

Hardgrave, B.C., Aloysius, J.A. & Goyal, S., 2013. RFID-enabled visibility and retail inventory record inaccuracy: Experiments in the field. Production and Operations Management, 22(4), pp.843–856.

Hardgrave, B.C., Goyal, S. & Aloysius, J. a., 2011. Improving inventory management in the retail store: The effectiveness of RFID tagging across product categories. Operations Management Research, 4(1–2), pp.6–13.

Hardgrave, B.C., Waller, M. & Miller, R., 2005. Does RFID reduce out of stocks? A preliminary analysis. Information Technology Research Institute, Nov 2005.

Hardgrave, B.C., Waller, M. & Miller, R., 2006. RFID's impact on Out of Stocks: A sales velocity analysis,

Riemenschneider, C.K., Hardgrave, B.C. & Armstrong, D.J., 2007. Is there a business case for RFID? Information Technology Research Institute, May 2007, pp.1–19.

Rizzi, A., Romagnoli, G. & Thiesse, F., 2016. A new framework for RFID use cases in fashion and apparel retailing. International Journal of RF Technologies: Research and Applications, 7(2–3), pp.105–129.

Zinn, W. & Liu, P.C., 2008. A comparison actual and intended consumer behaviour in response to retail stockouts. Journal of Business Logistics, 29(2), pp.141–159. Available at: http://doi.wiley.com/10.1002/j.2158-1592.2008.tb00090.x.

Zinn, W. & Liu, P.C., 2001. Consumer response to retail stockouts. Journal of Business Logistics, 22(1), pp.49–71. Available at: http://onlinelibrary.wiley.com/doi/10.1002/j.2158-1592.2001.tb00159.x/full.