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RFID ENABLED VISUALIZATION OF PRODUCT FLOWS: A DATA ANALYTICS APPROACH

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Complete Research

Abstract

Radio frequency identification (RFID) is an information facilitator that can directly improve decision-making; thus many retailers and suppliers have adopted it. A vast amount of RFID data streams has been gathered, however, it remains unutilized, or it is been exploited solely for inventory count purposes. This research proposes a way to analyze the immense volume of RFID data reflecting the behavior of products in retail stores, in order to produce information for inventory availability and inventory flows at different stages of the supply chain. We propose an RFID data analytics artifact that transforms RFID data captured in retail stores to the flows of the inventory/ products between locations in the stores. By mining the RFID data streams, we reveal the flow patterns of the products; these patterns correspond to the frequent product paths in the stores, and we provide them to the retailers in a visual manner. This unprecedented knowledge is valuable, because it can enable decisions ranging from shelves space allocation, dynamic pricing programs for slow-moving fresh products to product assortment. Furthermore, to testify artifacts' correctness and usefulness, we have put it in practice, using real data provided by an Italian fashion retailer, in order to show how it can really support such decisions.

Keywords: RFID data analytics, decision making, product flow patterns, fashion retail

[1] ELTRUN: The e-Business Research Center

1 Introduction

Radio frequency identification (RFID) assists retailers to look into the operation of their business processes, and appears to be an important generator of innovative business information that has led to various organizational benefits. RFID spurs lots of prospects for efficient management of supply chain processes and decision support (Dimakopoulou et al., 2014). Thus, RFID technology should be viewed as an information facilitator that can directly improve decision-making (Sellito et.al, 2007). It plays an important role in supporting logistics and supply chain processes. It can provide suppliers, manufacturers, distributors and retailers precise real time information about the products (Zhu et al., 2012). Over the past two decades, the retail industry has implemented RFID resulting in reported improvements in inventory productivity (Unger & Sain, 2015). RFID technology could be also utilized to improve product traceability and the visibility, however, many retailers and suppliers/ manufacturers have applied RFID solely for inventory management and inventory accuracy purposes (Hardgrave et. al, 2011, 2013; Thiesse & Buckel, 2015; Tijun et. al, 2015).

At the same time, business analytic techniques have been developed that can connect large datasets to enable broader and deeper analysis than previously possible (Provost & Fawcett, 2013; Phan & Vogel, 2010). As a consequence, data-driven decision making is now recognized broadly, and there is growing enthusiasm for the notion of "Big Data". Big Data analytics now drives near every aspect of our modern society, including retail industry, financial services etc. (Bertino et.al, 2011). Big Data research looks at how to analyze data in different domains with such characteristics; and in a way that generates deeper knowledge and adds value to the decision making process in businesses (Sharda, Asamoah, & Ponna, 2013).

Taking advantage of the new technologies, which allows us to process the immense volume of the RFID data streams, this research proposes how we can analyze the available vast amount of RFID data, reflecting the behavior of products in the retail supply chain, in order to produce information for inventory availability at different stages of the supply chain. We propose an RFID data analytics artifact that transforms RFID data captured in retail stores to the flows of the inventory/ products between locations in the stores. We mine the flow patterns; the frequent paths of products and provide them to the retailers/ suppliers in a visual manner. This unprecedented knowledge is valuable, because it can enable decisions such as, shelves space allocation to product categories, according to their moving rate. We have put the artifact in practice, using real data provided by an Italian fashion retailer, in order to show how it can really support such decisions.

The remainder of the paper is organized as follows. Section 2 describes the proposed methodology. Next, section 3 presents the application of our approach to real item level RFID data. Then, we highlight the decisions that could be supported by the mined knowledge. Finally, we overview this research's main outcomes; and discuss further research.

2 RFID Data Analytics Approach

2.1 Overview

This research has adopted the "Design Science" approach (Hevner et al. 2004). An artifact has been developed; it is an RFID Data Analysis Pipeline which consists of four phases. The proposed approach has been evaluated in practice; we used 6 month RFID data from a store of an Italian fashion retailer, to mine useful knowledge. Ultimately, the findings from the RFID data analysis aspire to give decision support to the Italian retailer and, generally, the apparel and fashion retail industry. Figure 1 depicts the proposed approach consisting of 4 phases: (A) Data Description & Preparation, (B) Modeling Product Flows, (C) Knowledge Mining, and (D) Business & Data Understanding. Business and data understanding phase is a "superset" of the other three phases; we need to apply it throughout the data analysis pipeline because the business goals need to be taken in account during the analysis, as well as the data derived from each step. Each phase has inputs and outputs; by refining the inputs of each phase, and passing through the entire pipeline's lens, we will extract the valuable knowledge which will be used to support decision making.

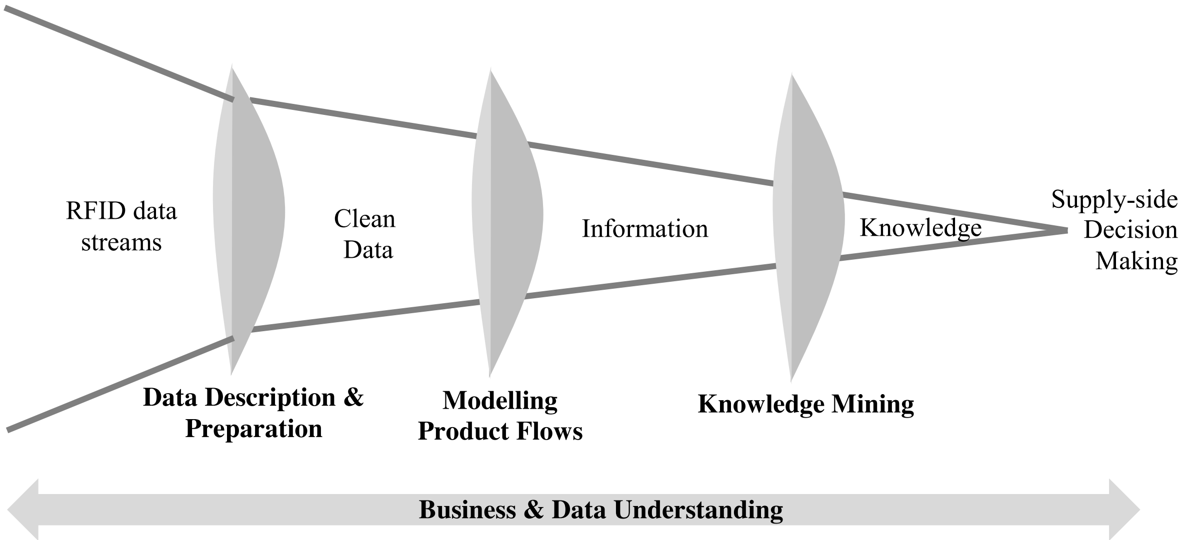

Figure 1. RFID Data Analytics Approach

2.2 Data Description and Preparation

The initial phase focuses on obtaining and exploring the dataset, having in mind the business objective, which is to extract knowledge to support decision making. The dataset needed to perform this analysis is RFID data that represent garments movements into the stores, made either by the customers or by the clerks while performing business processes and RFID-enabled processes such as replenishments, receiving, purchasing etc. We have to know the exact places of the products and the processes that are connected with these places (table 1). For example, we should know that a product, which is being uniquely identified by an electronic product code (EPC), has just been received in a specific time and it's in the backroom, or the product has been transferred from backroom to store floor, and then it is located in check-out desk as it is sold, and at the end it passes the electronic article surveillance (EAS) gate. Moreover, it could be useful to have additional characteristics of the stock keeping units (SKUs), for example if the RFID captions concern garments we could have garments' size, color, the product category they belong to, or in other cases we could have date of expire, products dimensions etc.

EPC	Location	Process	Time Stamp	SKU	Additional characteristics
xyz	backroom	receiving	4/7/2015 11:00	12443234323467	…
xyz	replenishment gate	replenishment	5/7/2015 9:30	12443234323467	

Table 1. Dataset Example

The dataset could be enriched with data captured by real time location RFID system (RTLS) i.e. exact store areas in the store floor. For example, a product X in time Y is in store floor in "A" store area, and then in time X+1 a customer took the product and transferred it to "B" store area, and then the same product entered the fitting room also with product Z. The last dataset could enlighten the knowledge extracted from the analysis and could reveal the whole benefits of adopting RFID in retail and applying data analytics in the derived dataset.

Data preparation covers all the activities to construct the final dataset. Hence, we have to select the appropriate RFID data that will be used in the forthcoming analysis, and clean the dataset. As it is well-known RFID data streams have a noisy nature, thus we have to de-noising them by eliminating duplicate values, inconsistences from the dataset, and corrupted values (Keller, et al, 2014).

2.3 Modelling Product Flows

A modeling precondition is to identify model's entities. This task is critical as it will help us to have a holistic understanding of the RFID system and the RFID-captured product movements. Thus, we have to identify the:

- Store locations the product movements take place. For example, backroom, sales floor, and their sub-locations. For example, the check-out, the replenishment gate, the EAS gate, sub-sectors in the store floor location etc.
- RFID readers. For example, RFID cages, replenishment gates, check-out readers, EAS gates, handheld readers etc.
- Business processes and RFID-enabled processes. For example, inventory, replenishment, check out, EAS gate, return, theft etc.

According to the RFID locations, the readers, and the processes take place in the store we have to identify the RFID captured product flows. It could be useful to create a graph in order to have a better visualization of these flows; this could be also used as input to predict garments' movements. In this graph we could depict the correct captured flows from a process and a system perspective, and the false product flows which lead to missing reads. This information could be used to detect the data quality issues, which derived from the readers' inconsistences; for example, if a product is being captured in the receiving, and then directly in the check-out, we assume that there is a missing read in the replenishment gate.

Concerning the data quality issues, it's critical to identify the false positive self joins. The self joins are more than one contiguous in time captures from the same reader. In the dataset, we may observe that the same EPC is read more than one time respectively from a reader during passing from a location to another. For example, a garment in the process "store floor replenishment" is read two times respectively. This seems to be right from a system and a process perspective, as it is legit the reader to capture the garment two times in a row within few seconds. But in these self-join cases maybe there are hidden false positive self joins. These joins concern wrong RFID reads from a process perspective. These are self-join reads which happen in greater contiguous timestamps, and lead to missing RFID reads. For example, a product which is read two times when passing from backroom to store floor, with a time difference of two days, this is not a right self-join read, since other missing RFID reads that intervene.

2.4 Knowledge Mining

Finally, we have to transform RFID data into decision making data, according to the business questions we want to answer. Indicatively we could:

- Calculate the mean times between the basic entities of the model, and the entities of the transition graph, in product categories, SKU level, colors, sizes etc.
- Calculate the product categories, SKU, colors, and sizes in fast, medium, slow, and no moving, according to the each product's speed history on the sales floor. By history speed we refer to the average time a product spends on the sales floor from the time it was moved there till the time it was sold
- Classify the product categories, SKUs, color, sizes in high, medium, low and no sellers according to their sales.
- Detect the missing SKUs from the store that are high sellers and fast movers.

- Detect the missing sizes and colors of a high seller category.
- Detect of the garments that frequently enter the fitting room but they aren't sold
- Detect the misplaced products

3 Experiment

In this section we apply the above method in real data provided by a fashion retailer, in the context of SERAMIS[2] EU project, in order to testify the method's effectiveness.

3.1 Data Description and Preparation

The dataset will be analyzed concerns garment's movements captured via RFID in a retail store collected from 27 May to 30 November of 2014. The first step of this phase is to select the data that will be used for the forthcoming analysis. We decided to use the information about store locations, RFID readers, RFID processes, garment sizes, names, and colors, as shown in table 2. Then, we had to de-noise the dataset. So, by eliminating duplicates, corrupted values and inconsistences, from the 307.243 initial record we continued the analysis with 99,89% (306.912 records) of them.

EPC	Location	Process	Readpoint	Time Stamp	SKU	Category	Product Name	Size	Color
urn:epc:tag:gid-96:31161137.20037.100004	checkout	Check out	checkout	2014-10-12 17:06:20.000	31161137020037	shirt	MOGOL	48	3
urn:epc:tag:gid-96:31161137.20037.100004	storefloor	Replenishment	replenishment gate	2014-09-17 16:26:09.000	31161137020037	shirt	MOGOL	48	3
urn:epc:tag:gid-96:31161137.20037.100004	backroom	Receiving	RFID cage	2014-09-04 11:17:15.000	31161137020037	shirt	MOGOL	48	3
urn:epc:tag:gid-96:31161137.20037.100004	storefloor	Inventory	handheld1	2014-09-23 15:33:33.000	31161137020037	shirt	MOGOL	48	3
urn:epc:tag:gid-96:31161137.20037.100004	storefloor	Inventory	handheld1	2014-09-30 16:07:23.000	31161137020037	shirt	MOGOL	48	3
urn:epc:tag:gid-96:31161137.20037.100004	storefloor	Inventory	handheld1	2014-10-06 12:01:59.000	31161137020037	shirt	MOGOL	48	3
urn:epc:tag:gid-96:10160339.60054.100003	backroom	Replenishment	replenishment gate	2014-08-18 13:30:32.000	10160339060054	cloak	LISA	42	5

Table 2. Sample of the selected RFID data

3.2 Modelling Product Flows

Our first goal is to depict the RFID streams in a graph, and display garments RFID-captured movements. Identifying the model's entities as shown in figure 2, we have (A) the store locations (B) the RFID readers, and (C) the RFID processes. Concerning the store locations, we have the backroom, and the backroom entrance from where the garments enter the store, the store floor, the replenishment gate, which is the intermediate location between backroom and store floor, the store aisles, where the garments are displayed, and the check-out desk where the garments are moved during the purchasing process. Each store location has RFID readers. We have two kinds of readers, the stationary and the non-stationary readers. The last of them could be used either in backroom or in store floor for inventory control. Moreover, we have 7 RFID processes; each process is connected with a reader. In the next paragraphs we will eliminate those processes that interact with the "out store environment" i.e. C5, C6, C7. Last but not least, at this point we have to mention that the inventory processes may happen by clerks at any time via using handhelds. In figure 3 are shown the entities of the model in the store layout.

[2] Sensor-Enabled Real-World Awareness for Management Information System (http://seramis-project.eu)

A. Store locations:
   1. Backroom
      i. Backroom Entrance ∍ Backroom
   2. Replenishment Gate (an intermediate store location)
   3. Store floor
      i. Checkout Desk∍ Store Floor
      ii. Store Aisles ∍ Store Floor

B. RFID Readers:
   1. Stationary:
      i. RFID Cage (is placed in location A1i)
      ii. Replenishment Gate (A2)
      iii. Checkout reader (A3i)
   2. Non-stationary:
      i. Handhelds: (A1,A3ii)

C. RFID Processes:
   1. Receiving (B1i)
   2. Replenishment (B1ii)
   3. Inventory (B2i)
   4. Checkout (B1iii)
   5. No RFID in Arrival (B1i)
   6. Shipping to Distribution center (B1i)
   7. Shipping to other Stores (B1i)

Figure 2. Basic entities of the model-graph

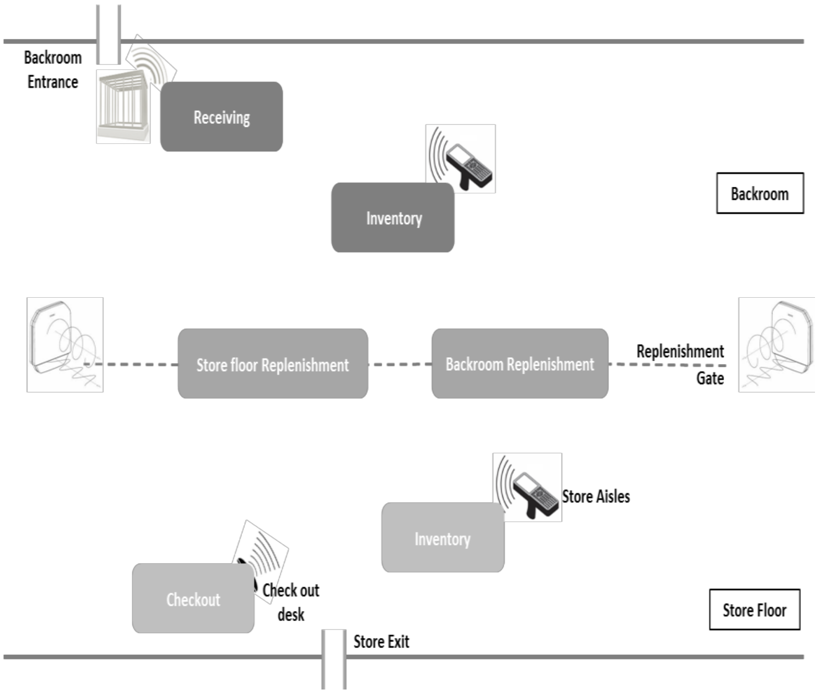

Figure 3. Model's entities in the store's layout

According to the recognized model's entities, we identify the RFID-captured garments' movements, and we create the garments' flow graphs. In figure 4 is shown the garment's graph which concerns the correct flows. The number in each node represents the RFID captured garments at the location. The green arrows represent the garments' correct flows. The flows from a node to the end, show the number of garments which passed from this node and stayed there, so during the time frame of the given dataset we can't detect them in any other node after that event. For example, at figure 4 we can notice that the majority of the garments (70.211) had been captured for first time at the backroom entrance during the receiving process via the RFID cage. At about 35% of them (24.125) stayed at the backroom, and had never been displayed at the store floor. We have only eleven captures in the backroom during the inventory count process, via the handheld. At about 42.852 garments passed from the backroom to the store floor through the replenishment gate, and 27.720 garments had been sold.

As far as the self-loops of the replenishment transitions are concerned, we came to the conclusion, that they are also divided into right flows, and false positive flows. The right self-loops are those that the time from the first timestamp (t_1) until the next one (t_{1+1}) is less than one minute. This means that the garment stayed in this location and by mistake it had been read more than once. The above also happens for the RFID cage self-loops. We assume that the other self-loops at the replenishment gate are wrong. This happens because if t_{1+1} - t_1 is more than one minute maybe between these periods of time there are missing intermediate reads. Concerning the self-loops of the inventory nodes, we accept that all of them are right, because as mentioned before, it's possible to check the inventory a lot of times during a period, before the garment reach to change a node. Last but not least, in each transition graph it could be also meaningful to convert the actual number of garments pass from each node into percentages, in order to show the probability of which will be the next node of the garment the moment t+1.

In the same context, we also depict in figure 5 the garments' false flows. By examining the wrong flows we could figure out inconsistences in the RFID readers. Thus, we could improve the quality of the data derived from the RFID system.

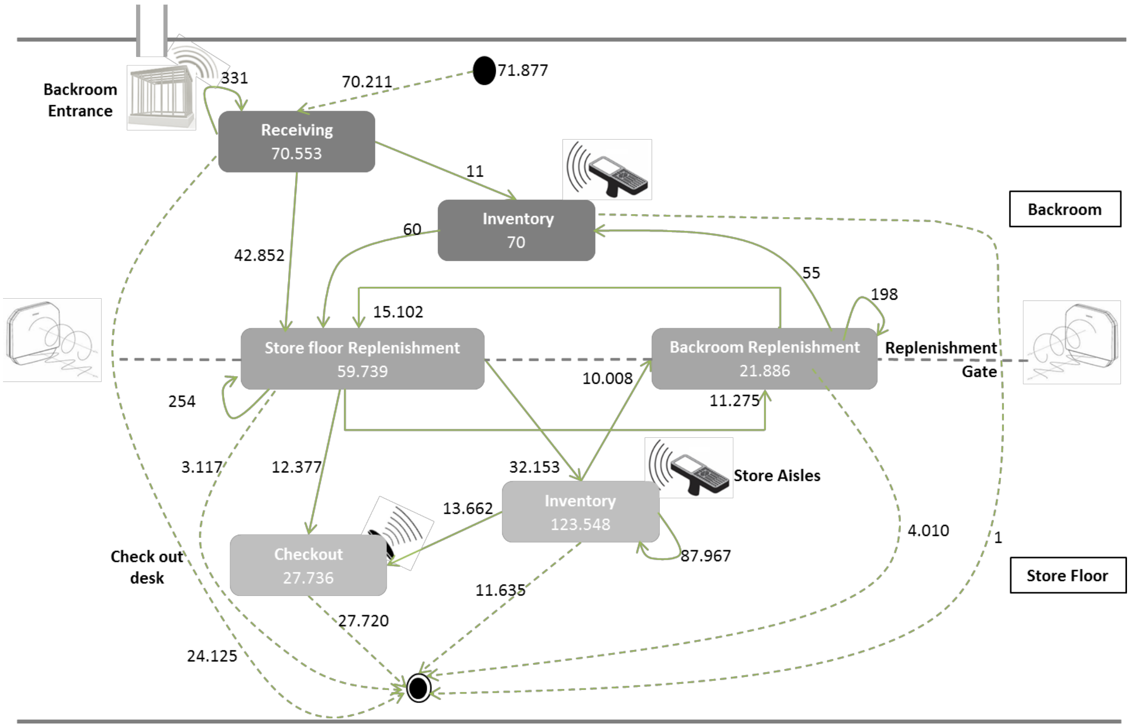

Figure 4. *Garments Transitions Graph- right flows*

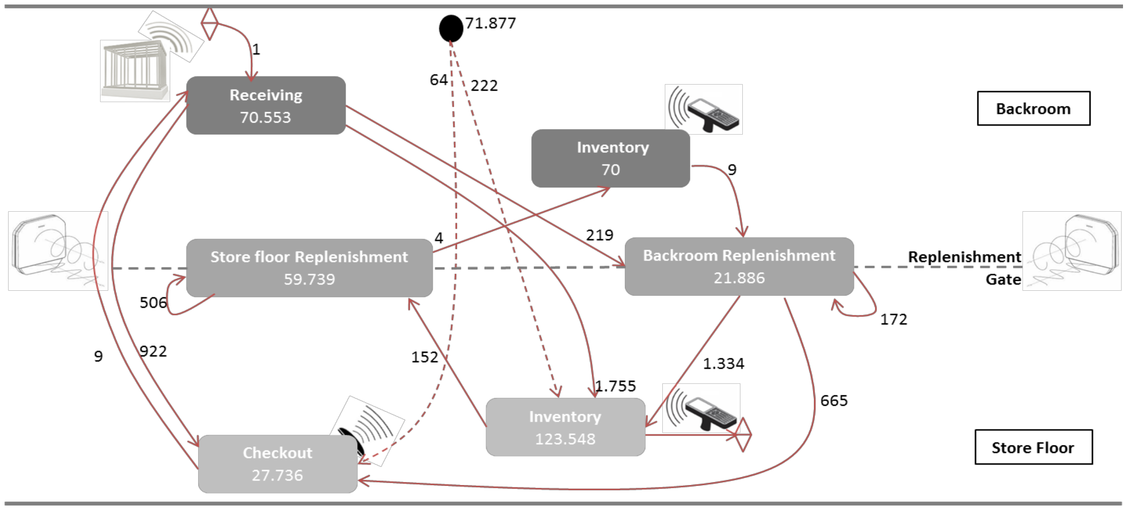

Figure 5. *Garments Transitions Graph- wrong flows →missing reads*

3.3 Knowledge Mining

After eliminating from the dataset the false flows we need to transform the RFID data into decision making data. In this section we will show what knowledge we could mine from the given dataset, which business questions we could answer, and what business reports we could support. From the data provided we could extract the average days the garments stay in each location before being transferred to another. For example, in figure 6, we could figure out that 27.068 garments stayed on average 2 months (60,49 days) in the store until they have been sold. This report could be useful for the store manager in order to observe garments states, and detect delays. Moreover, it would be more meaningful to have this kind of report per product category, or per color, size and SKU, and this question could be answered from the given dataset.

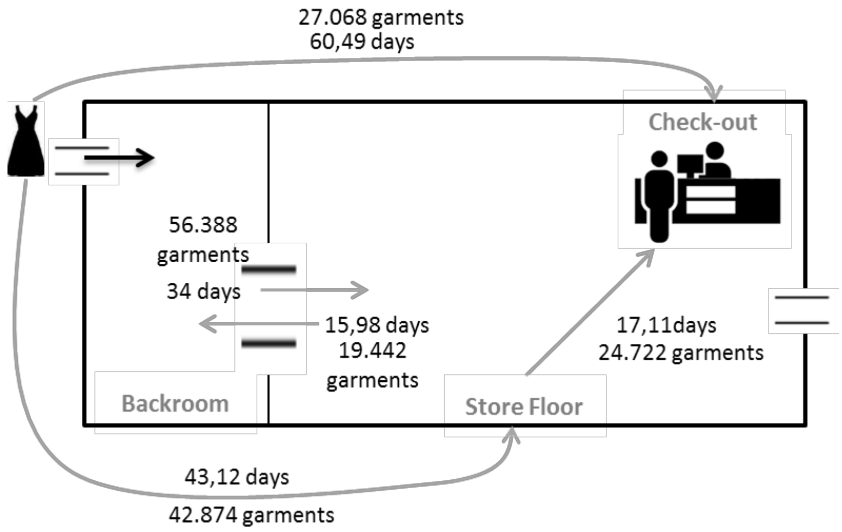

Figure 6. Average days per location

Furthermore, we could categorize the garments in fast, medium, slow, and no moving, according to the average time from the moment they being transferred from the backroom to the store floor, till they have been sold. This could be helpful for the store's manager to determine replenishment strategies. According to five-number summary (box plot) as shown in figure 7 the garments that stayed from 4,33 to 10,88 days in the store floor before they been sold are considered as fast moving etc. Then utilizing the box plot we created figure 9 that depicts the product categories in classes according to how fast they are bought by customers. The green product categories are the high moving ones, the orange are the medium moving ones, and the red are the slow moving ones. At this point we have to mention that before calculating the five-number summary the outliers had been eliminated. Outliers are product categories that moved from store floor to check out only a few times (i.e. less than 20). This report is useful to be combined with the top selling product categories (figure 8). This way the manager will observe and compare the fast moving and the top selling categories. This information could be utilized, for example, to decide the space allotted for each category, the number of items per color or per size that should be displayed in the store floor. Moreover, the categories which are unsold in the store floor are labeled as "no moving"; in our case these categories are "leather skirt" and "short trousers". The following figures concern the results extracted by all the given timeframe (6 months), thus it could be also useful to have this kind of information daily, in order to have a better visibility of the garments.

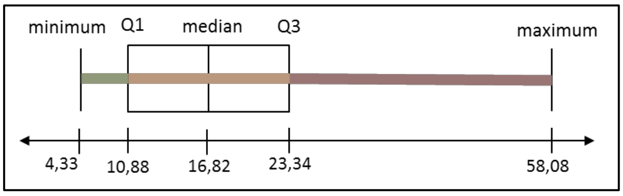

Figure 7. Product Categories – Box Plot in average time from store floor to check out

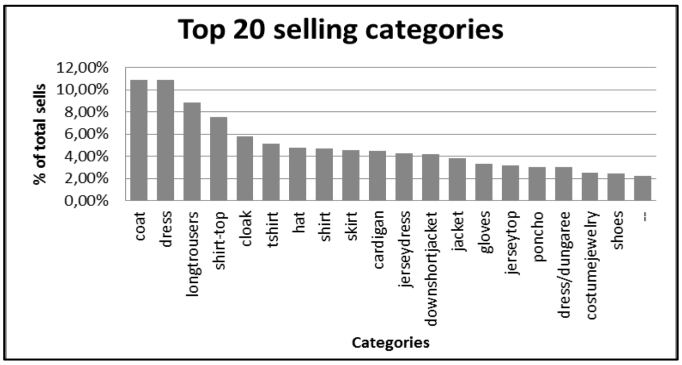

Figure 8. Top selling product categories

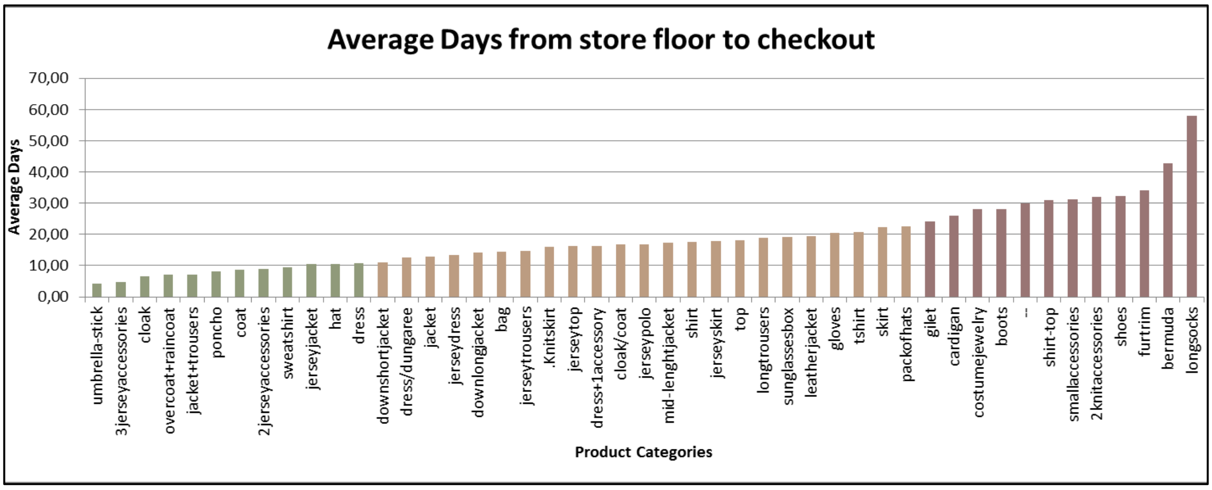

Figure 9. Product categories classification based on average days from store to check out

The same reports as above could be also generated per sizes and per colors. For the SKU level it could be more useful to produce a table with the fast moving SKUs compared with the top SKU sellers, as shown in tables 3 and 4. The timespan used for these descriptive is all the available dataset i.e. from 27 May to 30 November of 2014.

SKU	Category	Product Name	Size	Color	Average Days to be sold
63740141050601	poncho	NANO	NULL	60	0,13
63740141050031	poncho	NANO	NULL	3	0,60
63740041050601	poncho	NAFTA	NULL	60	1,26
63740041050151	poncho	NAFTA	NULL	61	1,60
83740643050421	poncho	EMILIO	NULL	42	3,34
65140343050601	bag	KITTI	36	60	4,33
65340132050011	umbrella-stick	MAN	36	1	4,33

Table 3. Fast moving SKUs

SKU	Category	Product Name	Size	Color	No of Garments
85749840050011	hat	CAPP-AI	36	1	1027
85749830050011	hat	CAPP-AI	36	1	108
65340132050011	umbrella-stick	MAN	36	1	41
57560838060012	costume_Jewelery	AMICO	NULL	1	35
63740041050151	poncho	NAFTA	NULL	15	34
63740041050601	poncho	NAFTA	NULL	60	33
83740343050421	poncho	EROS	NULL	42	32

Table 4. Top Selling SKUs

Furthermore, it would be helpful for the manager to have a list with the SKUs, from which they have a lot of pieces, but are kept in the back store without having a presence in the sales floor, as shown in table 5 from the 6 month data we analyzed.

SKU	Category	Product Name	Size	Color	No of Garments
26060629020012	various	PEPE	NULL	1	20
48040428030041	sunglasses	CALYPSO	NULL	4	17
45260224060011	shoes	1RIVOLO	39	1	16
27240527030013	smallaccessories	SESTRI	NULL	1	15
47540646050281	costume_Jewelery	CRI8	36	28	15
48040128030023	sunglasses	CALESSE	NULL	2	15

Table 5. SKUs that remain in the backroom without having a presence on sales floor

Moreover, another interesting report would be to present the "no moving" SKUS that are presented on the sales floor, but are for a long period unsold. For example, for the 6 month data in table 6 are shown SKUs that stayed from 4,5 to 5 months unsold on the sales floor.

SKU	Category	Product Name	Size	Color	Average Days Unsold
53460139060014	cardigan	GHIANDA	NULL	1	160,08
90140136030013	cloak	LISA	40	1	159,65
60140430030027	cloak	DISCANTO	48	2	159,30
90140136030014	cloak	LISA	42	1	156,25
47241037030013	smallaccessories	AMMIRARE	NULL	1	154,88
90140136030012	cloak	LISA	38	1	149,28

Table 6. SKUs that are present at the sales floor for a long time unsold

The above could be utilized in cases with little space on the sales floor in order to achieve a better allocation of the available sales area. Moreover, in these cases if we don't have "no moving" SKUs, we could move "slow moving" SKUS to the back room, as shown in table 7.

SKU	Category	Product Name	Size	Color	Average days to be sold
77940130040224	boots	LILLA	39	22	162,00
33430930040325	cardigan	MALESIA	NULL	32	153,71
60130330040102	cloak	TOPAZIO	19	10	151,83
63630930040165	shirt-top	AMARENA	NULL	16	145,88
57960533060023	boots	CARDATO	36	2	143,92
15860233060032	furtrim	BUONA	NULL	3	143,00
23430330040794	cardigan	MIA	NULL	79	142,92

Table 7. Slow moving SKUs

Another interesting report is to generate a daily list with the lasts days' high sellers and/or fast movers. The high sellers is an information that could be derived from the inventory counts without using RFID data, but fast movers that could enrich the replenishment reports could only be derived from the RFID data. This list would be useful to depict the garments' remaining pieces in the store area and the remaining pieces in the store floor. It's important for the manager to be able to detect:

- The garments that are not present on the sales floor but are available in the backroom (red color in table 8).
- The garments that should be refilled, as there are only few pieces remaining on the store floor (orange colors in table 8).
- The garments that are not available in the whole store area (grey colors in table 8).

The manager could use this type of information to order from the other stores these garments, and/or to bring on the store floor other garments that have the same characteristics (size, color, category etc.) with the unavailable garments (grey colors).

SKU	Category	Product Name	Size	Color	Times purchased	Remaining pieces	Store floor pieces
31161137020037	shirt	MOGOL	48	3	10	1	0
65140643050601	bag	KUBO	36	60	3	11	1
80140440050042	cloak	1NADAR	38	4	3	2	1
60160139060034	cloak	FARNESE	42	3	2	3	1
89440240090423	jerseytop	XMULTIAR	NULL	42	3	0	0
10861423060012	coat	SORTE	38	1	2	0	0
61340730040743	longtrousers	RIALTO	21	74	2	0	0
30860526020015	coat	LUCERNA	44	1	2	0	0

Table 8. SKU daily replenishment list – based on the high sellers and fast movers on 26/08/2014

4 Supporting Decision Making

This section discusses how the knowledge extracted from the above approach could be utilized to support managerial and replenishment reports in fashion and apparel retail stores.

4.1 Managerial Reports

Specifically, the reports concerning the transitions graph (figures 4, 5) could be utilized by the manager not only to identify readers' inconsistences, but also to have a better visibility of the garments transitions in the store. Also, this kind of information per SKU or even per product category level could be used to predict garments' movements.

Furthermore, reports such as the mean times between the locations and the product transitions per product category (figure 6), or per color, size and SKU, could help managers to have a more detailed visibility of the garments. By categorizing the garment categories (figures 7, 9), or even the sizes and the colors, into fast, medium, slow, and no moving, according to their average time from store floor to check out, and by combining this report with the top selling products (or sizes, or color), the manager could decide the space allotted for each garment category, the number of items of each color, or size should be in the store floor. Also, by combining the above information with the top selling and fast moving SKUs he could identify the SKUs that should always have presence in the sales floor, as these satisfy the shoppers' preferences (tables 3, 4). Last but not least, the reports about the "no moving" SKUS, that are presented at the sales floor, but are for a long period unsold (table 6), could be utilized in cases that there is not enough space on the sales floor and there should be a better allocation of the available sales area. In addition, in these cases if we don't have "no moving" SKUs, we could move the "slow moving" SKUs to the back room (table 7). The above information could be also used by the manager to promote these garments ("garment of the day"), or even to design dynamic pricing strategies to get rid of them. This kind of information could also be used to support replenishment reports.

4.2 Replenishment Reports

Respectively, the SKUs found to be "no moving" or "slow moving" for a long period, could be also be reported in the replenishment report in order to transfer them back to the backroom. Thus, we may gain some space on the sales floor for those garments that are kept in the backroom without having a presence on the sales floor (table 5). In addition, the high selling and fast moving garments which are not present on the sales floor but are available at the backroom, the high selling and fast moving garments that should be refilled, as there are only few pieces remaining on the store floor (table 8), could also be used to support daily replenishment reports. Last but not least, to avoid out-of-shelf situations, a report with the high selling and fast moving garments that is not available in the whole store area could help the manager either to order them from other stores, and/or to bring garments that have the same characteristics (size, color, category etc.) on the store floor.

5 Conclusions & Discussion

This research looks into item level RFID data captured in retail stores and introduces a new way of utilizing these datasets. We show that RFID technology is more than a tool for obtaining inventory counts in the locations of the retail stores. We develop an approach for RFID-enabled visualization of inventory/ product movements/ flows in the store. We are no longer interested only on the quantities of products positioned on shelves, passing through backroom entrance etc. We reveal the products movements' behavior in order to support decisions ranging from shelves space allocation, dynamic pricing programs for slow-moving fresh products, to product assortment. In the context of SERAMIS EU project, we put this RFID data analytics module in practice with real data provided by a fashion retailer.

We intend to obtain and use more RFID data to support a bigger range of business decisions. For example, we can detect the patterns and the affinities of the garments shoppers try on from the fitting rooms' RFID data. Customers frequently enter a garment store having in their mind (a) specific shopping goal(s), but often they don't purchase the garments they visit the store for. Perhaps the garments didn't fit them, or they didn't find the size they looked for etc. For these reasons, it could be meaningful to compare the garments' patterns and sales affinities derived from the point-of-sales (POS) data, with those derived from the fitting room data, as this kind of data reflects the initial and maybe the real shopping goals of the consumers. Garments patterns derived from the fitting rooms may be different of those derived from the check-out; these could convey signals to the managers that there are selling gaps. Use of RFID technology at the POS level can be used to generate demand trends and build a probabilistic demand pattern. This application is invaluable for retail apparel industry with high levels demand uncertainty (Zhu et al. 2012). Moreover, the fitting room RFID data can reveal those SKUs that are often detected in the fitting room, but they don't reach the check out. Having this kind of information, we can design promotions and even dynamic pricing strategies. In general, the item level RFID data from a real time location system (RTLS) all over the store could enlighten the value and the decisions could be extracted from the system, as it could offer a greater traceability and visibility of the garments at any time (Tijun et. al, 2015; Zhu et al., 2012). Indicatively, some of the advantages are that the manager could obtain a fully inventory visibility, also misplaced garments could be detected etc. Last but not least, by combining the RFID data with other data sources, such as weather data, we could enrich replenishment reports; not accidentally umbrellas are the fast sellers in figure 9.

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