Journal of Retailing and Consumer Services 47 (2019) 184–194

Contents lists available at ScienceDirect

Journal of Retailing and Consumer Services

journal homepage: www.elsevier.com/locate/jretconser

A business application of RTLS technology in Intelligent Retail Environment: Defining the shopper's preferred path and its segmentation

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ARTICLE INFO

Keywords:
Shopper behaviour
Intelligent retail environment
RTLS technology

ABSTRACT

Over the last few years, shopper behaviour analysis in the retail environment has become an interesting topic both for managers who want to see the tangible impact of their trade marketing activities and researchers who are trying to identify new patterns or confirm known trends in this field. In such a context, technologies today play a central role, because of the possibility of implicitly observing how shoppers move inside the store, and collecting a wide data-set, through an unbiased approach, free from distortion. In this paper, we will describe the major outcomes from a study based on data collected through an innovative technology, Real Time Locating System (RTLS). We base our conclusions on a data-set, collected over three months of observations, composed of more than 18 million records transmitted by RTLS tags, monitoring the entire path of each shopper throughout the entire store area. The outcomes of our study are 1) the identification of the store's best performing areas based on traffic and dwell time metrics, 2) the development of a novel method to estimate the probability of in-store shopper paths and 3) a preliminary shopping trip segmentation.

1. Introduction

Shopper behavioural analytics has been receiving increasing attention over the last few years. Observing how shoppers behave within different store and shelf layouts provides a fundamental insight for industries and retailers who want to optimize the revenue/cost equation by enriching the in-store experience of their shoppers.

Despite the growth in e-commerce and digital retailing, the physical store still maintains a central role in the shopping journey. However, even the physical store needs to be adapted to shopper dynamics and emerging desires. A set of proved strategies has to be activated at the point of sale, with the ultimate goal of satisfying the value equation, attracting more shoppers more frequently and with bigger basket sizes.

The modern retail sector still considers retailers, manufacturers, and shoppers as held apart like three different actors who operate independently of each other. Manufacturers produce goods to sell, retailers manage the stores to sell the goods, and shoppers enter the store to buy things. For decades, i) the retailer's belief that profits come from brand promotions rather than from the shoppers themselves has led to placing a greater emphasis on price strategy than on the customers themselves; ii) brand manufacturers have invested a great deal in analysing shopping behaviour in order to understand consumer outside the store. Only in the last few years has there been a change in paradigm: now both retailers and manufacturers have understood the great opportunities for improving sales and profits arising from understanding shoppers' behaviour inside the store.

In the meantime, the bar to accessing analytic solutions has been lowered, allowing small and medium-sized companies to exploit the value of data and increasing competition. Analytical solutions that, up to a decade ago, constituted a key benefit and added value for a few market players, are today accessible also to smaller players, who can effectively have access and apply those insights to their decision-making processes. In this direction, the use of technologies has improved relentlessly and revolutionised a way to generate insights to answer the key business questions of the industry and the retailers. Since the retail sector has increased in complexity (multiple formats across a range of countries), numerous studies have been carried out with the aim of investigating how shoppers behave and how the information collected inside the store can be useful in creating the best strategies to improve sales and profits.

In this paper, we present the results of an analysis of how shoppers navigate a store in terms of 'path to purchase'. The study is based on data collected through an innovative tracking system (RTLS). In more detail, RTLS is based on ultra-wideband technology, which provides the

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https://doi.org/10.1016/j.jretconser.2018.11.005
Received 16 March 2018; Received in revised form 6 November 2018; Accepted 12 November 2018

use of several ultra-wide band (UWB) antennas suitably positioned inside a predetermined area and powered battery tags free to move inside the area (Contigiani et al., 2016). The implications of this research are both theoretical and managerial. Regarding the theoretical implications, this study contributes to the literature of shopper behaviour analysis focusing on better understanding shopping patterns through a systematic and quantitative approach. From the manager's point of view, we present actionable metrics to evaluate the store's performance and a novel method to identify the shopper's type based on their path to purchase.

This paper is organized as follows: In Section 2 we introduce an overview of the used analytical approaches and explain how the results can be used to help business succeed in the retail environment. In Section 3 we present a description of the RTLS system with details on the related works and methods for indoor localization and tracking (Section 3.1) and specific insights into its application in the retail environment (Section 3.2). In Section 4, we present the preliminary output for shopper in-store path identification with details on: in the Section 4.1 density maps and average time spent in each store department are illustrated, while in Section 4.2 we explain shopper preferred paths and their preliminary segmentation. Conclusions and recommended future research are proposed in Section 5.

2. Literature and research questions

Understanding and improving the shopper experience has become a primary topic for both manufacturing and retailing. It has shown itself to be, furthermore, a central topic for academic research.

Many studies have been carried out touching different aspects, applications, and consequences of shopper behaviour. Earlier studies usually tried to decode the shopper's buying behaviour patterns. The aim of such studies was to determine who, where, what, when, and how the purchase process works and how shoppers responded to sales promotion activities (Applebaum, 1951; Stern, 1962; Kollat and Willett, 1967; Frisbie, 1980) while others focused on the key drivers of shopping behaviour (Tauber, 1972; Inman et al., 2009; MacKay, 1973).

In-store shopper interviews represent one of the most popular techniques for measuring in-store behaviour. Normally, with this approach, shoppers are asked to answer questions and recall the path followed in their last shopping visit. However, validation done on real shopper's pedestrian flows indicate that such a technique, based on claimed answers, led to unacceptably high levels of inaccuracy due to the ‘autopilot’ approach shoppers follow over their standard shopping trips and the related very low level of recall (Young and Hetherington, 1996). Moreover, these methods of data collection are quite demanding in terms of both administration and respondent burden and may be sensitive to bias, particularly if we speak about data on the sequence of stores visited and the route taken, because of the respondent's memory (Moiseeva and Timmermans, 2010).

Other common techniques involve the manual tracking of a shopper round a store and tracing the shopper's path on a store map, monitoring shelf and product interactions, recording contacts with sales assistants, tracking secondary locations and display noticeability, etc. The recorded data are analysed and an approximation for the shopper traffic and behaviour is obtained. This observational data can provide a good estimate for shoppers’ habits, especially if used in the context of repetitive low involvement shopping trips (Adler and Adler, 1994). Overall, as demonstrated by numerous researchers, real observations of shoppers in-store have a higher validity than the experiments in laboratory environments (East and Uncles, 2008; Kwai-Choi Lee and Collins, 2000; Rust, 1993; Scamell-Katz, 2012). However, we also know that manual techniques are extremely labour intensive, time consuming, and remain limited to small subset of shoppers, a specific period of time, and to specific store areas, departments or categories. It is difficult and expensive, if not impossible, to use those techniques for a full and comprehensive view of in-store behaviour.

Because of these limitations, it is recommended to use passive methods to gather the required implicit observations to really decode mass in-store shopper behaviour. In this context, the term ‘passive’ has the same meaning as in Moiseeva and Timmermans (2010), where, unlike what happens in interviews, respondents do not have to provide detailed data about their shopping behaviour in the environment of interest. Such technologies, like RFID (radio frequency identification), RTLS, GPS, and cell phones, although not necessarily error free, provide data about the routes and stops and constitute important inputs required for models of pedestrian behaviour, but of course are also relevant for retail managers.

Advanced technologies have been successfully applied in retailing with the dual function of both providing numerous and useful information on the shopper's behaviour for the implementation of more efficient and customized marketing strategies and improving the costumer's shopping experience. In studying in-store shopper paths, the advent of new technologies has allowed both researchers and retailers to better analyse the underlying patterns of shopping behaviour in retail environments through the implicit observation of shoppers’ heterogeneity.

Some studies using RFID technologies have been developed in recent years (Sorensen et al., 2017; Larson et al., 2005; Hui et al., 2009; Moiseeva and Timmermans, 2010).

In particular, Sorensen conducted a multi-measure approach for an analysis based on a large number of shops and store visits by using RFID tracking system. In his analysis, in order to define general shopping patterns, three related metrics were formulated: i) the proportion of the store visited on a shopping trip, ii) the number of items purchased per shopping trip (basket size), iii) the amount of time spent in the store. The results of that analysis provide manufacturers and retailers with an important tool for the efficient management and design of retail outlets and at the same time for the implementation and evaluation of shopper marketing programs (Sorensen et al., 2017).

Larson presented an analysis of in-store consumer paths based on RFID tags located on their shopping carts. The analysis was performed using a multivariate clustering algorithm able to handle data-sets with unique spatial constraints, allowing taking into account physical impediments such as the location of aisles and other inaccessible areas of the store. The analysis highlighted the presence of three clusters, based on shopping time. By incorporating the time dimension of the shopping path into the analysis it was possible to note that most shoppers tend to only travel select aisles, and rarely tend to consider the dominant travel pattern. That analysis involved a technical and analytic clustering effort that focused only on travel patterns without regard to purchasing behaviour or merchandising tactics (Larson et al., 2005).

Also Hui et al., using a system based on RFI technology (PathTracker (Sorensen, 2003)) fixed under each shopping cart, examined the shopping paths using the travelling salesman problem (TSP). There, the TSP-path is defined as the shortest route that connects the entrance, all the products that a shopper purchased, and the checkout counter. Each shopper's observed behaviour is compared with their TSP-path, focusing on two types of deviation (order and travel deviation) in order to analyse the relations between purchasing behaviour and the characteristics of the shopping path (Hui et al., 2009). That study focused on the identification of patterns of the interrelation between order deviation and the other characteristics of the trip.

By using GPS technologies, another study of shopping trips in terms of retail location, traffic flows, and duration of the trips, was developed by Moiseeva and Timmermans. They used a Bayesian belief network (BBN) that, starting from the input of information about a particular observed outcome, provides some examples of how the visitor's shopping patterns and behaviour can be interpreted in terms of different themes (such as the duration of the shopping activities, identification of the location of each activity, transportation mode used, purpose, familiarity with shopping environment, and spatial pattern) (Moiseeva and Timmermans, 2010).

In the present paper, we carry out an analysis of shopper movement inside the store by using a data set collected via an innovative RTLS system with extremely high location precision. This technology gives us the possibility of monitoring all store areas, covering a full store map, and collecting data over a continuous and long observation period. This is the first time it has been used in this field of application. Such system automation allows extending the observation period to months or even years, continuously monitoring the store traffic and measuring the impact of promotional activities over time, as well as their seasonality and other influencing factors. Compared to standard research techniques (Page et al., 2018), the system makes possible gathering more precise and robust observational data. Furthermore, in the topic of passive consumer behaviour analysis, we introduce a novel method to analyse shopping paths, with the aim of creating an empirically based theory for preferred in-store shopper behaviour with a careful focus on state dependence, since choices made earlier in the path must have a great deal of influence on later choices, as shoppers cannot teleport from one part of the store to another. This will allow a more precise study of the key areas of the store and consequently marketing activities that may influence travel in a particular direction. In conclusion, the aim of our present study is twofold: from a general point of view, we analyse common patterns of shopper behaviour, and from a specific point of view, we deeply explore the real dynamics of the store and its departments.

3. Method: RTLS technologies

RTLS is an innovative system for use in trade marketing research. In this section, we will introduce an overview of the real-time tracking system application in an indoor context. In particular, in Section 3.1, we will provide details for the reasons behind our choice for a tracking system based on ultra-wideband. Then, in Section 3.2 we will provide a brief explanation of the RTLS system and how the data-set was collected.

3.1. The advantages of ultra-wideband technology for the retail environment

The most important requirements for a positioning system were summarized by a study, conducted in 2007, by the National Institute of Standards and Technology (NIST) (Gentile and Kik, 2007). These are: positioning precision below one meter; functioning at all locations and under all conditions; no training required on site; stability against structural changes, and limited costs. Furthermore, several criteria were identified in order to quantify the performance of different positioning systems. They can be classified as follows (Farid et al., 2013):

- accuracy, the most important requirement for a positioning system. This is determined by the mean distance between the estimated location and the real location;
- responsiveness, a measure of how quickly the position of a moving object is updated. If we are working with a quickly moving target, a rapid updating is a ‘must have’;
- coverage, strictly related to the accuracy and determined by the network coverage for a specific area. With this parameter we can measure the size of the monitored area and evaluate the performance of a positioning system at covering that area;
- adaptiveness, the ability of the positioning system adapt to environmental changes. The adaptiveness is higher if the locating system is able to provide a correct positioning even in the case of environmental changes, with no calibration required;
- scalability, another key parameter in the system design phase. If a system is scalable, it can operate with a larger number of locations and a larger coverage and be able to easily manage multiple variables;
- complexity – this criterion refers to the signal processing algorithm used to estimate the position. A very complicated algorithm and related accuracy are elements that can significantly affect the overall cost of the system.

Obviously, these criteria assume different degrees of importance depending on the specific applications for the positioning system (Fuchs et al., 2011). In the last few years, a wide set of tracking technologies have been proposed, such as Global Positioning System (GPS), Radio-Frequency Identification (RFID), cellular based, WLAN based, Bluetooth, ultra-wide band (UWB), and many others (Liu et al., 2007), but they can be chosen according to the intended use. One of the most successful has been GPS. However, due to the scarcity of GPS signals and the high HW costs, this technology can not be considered for broad use indoors (Zeimpekis et al., 2002) or in urban canyons where the calculation of the position is not univocally determined and there might be no signal. Cellular-based systems are mainly used to estimate the user location for outdoor applications. However, this technology can be used for indoor positioning systems if the building has several base stations or one base station with a strong RSS signal received by indoor mobile clients. The main limitation of this system is its generally very low accuracy, which greatly depends on the cell size.

A very popular technology in public hotspots and corporate locations, mainly in the last few years, is the Wireless Local Area Network (WLAN). This technology is not suitable for localization applications since the typical WLAN positioning systems using RSS have low accuracy, about 3–30 m, with an updating rate within the range of a few seconds.

Bluetooth technology has, compared to WLAN, a lower gross bit rate. Its range is also shorter. It supports many different networking services and each device has a unique ID. Bluetooth is included in most phones and personal digital assistants (PDAs). However, it is necessary that all devices have their Bluetooth active, and this is not always the case.

Radio-Frequency IDentification (RFID) is a technology for automatically identifying and tracking tags attached to objects, using an electromagnetic transmission to an RF compatible integrated circuit. This kind of system has many basic components. It can be passive or active (Liu et al., 2007).

Ultra-Wide band (UWB) is a radio technology for short-range (< 1 ns), high-bandwidth communication, with resistance to multipath interference, and a low duty cycle. The advantages of this technology, as presented by (Gezici et al., 2005), are: (1) compared to RFID systems, which use only single bands of the radio spectrum, UWB simultaneously transmits signals on multiple frequency bands (from 3.1 to 10.6 GHz); (2) unlike RFID, UWB signals are transmitted with a shorter duration, consuming less power and can operate over a wider range of the radio spectrum; (3) UWB and RFID can operate in the same area without interference thanks to the differences in signal types and radio spectrum; (4) the UWB signal is able to pass through walls, devices, and clothes, with no interference; (5) UWB technology has high values of indoor location accuracy, near 20 cm, not achievable using conventional wireless applications (RFID, WLAN and others).

Our system is based on UWB technology, because of its suitability for indoor locationing Koyuncu and Yang (2010) and for applications that require a high level of precision in real time for 2-D and 3-D localization.

3.2. Overview of the RTLS system and the data-set

An RTLS system based on the UWB technology has been integrated and tested in a retail environment (Paolanti et al., 2017; Contigiani et al., 2016; Sturari et al., 2016). The store in which the data-set was collected is a German supermarket, during business hours, where the UWB antennas were suitably placed in the area to be monitored and the tags had been installed on shopping carts and trolleys. The RTLS tracking process and construction of the data-set can be divided into three steps: (1) monitoring the path of the shoppers in the store via the tags and anchors, (2) sending the tracking data collected from the RTLS server to a cloud server, (3) processing and storing the data in a database. For the phases of (1) monitoring and (2) transferring the data to the cloud, the tracking system comprises:

- anchors that are static devices (antennas) with known positions, placed in the dropped ceiling of the store, to form a homogeneous grid in order to cover the entire store. The anchors gather signals from the tags and forward this data to the RTLS server;
- tags that are used to track mobile devices. They send data to the anchors at a specified transmission rate and they also send a broadcast message that is received by the anchors in a communication system;
- an RTLS server that collects data from the anchors, estimates the 3D positions of the tags, and sends these to the cloud server. A software application has been developed to collect the following information from the stream: master ID; tag ID; position coordinates (x, y and z); battery level of the tag, and timing information.

In phase (3) of data processing, all the possible anomalies and noise collected by the system are filtered out and two main assumptions have been made:

- the points with an attraction time inside a department less than 5 s and those shop trajectories traversed in less than 2 min, are filtered out since they are too short and not suitable for this analysis;
- a cart or basket stopped for 5 or more minutes is assumed to have been taken by another shopper, so we have a new trajectory.

4. First output of RTLS

In this section we present our first effort at an RTLS post-processing analysis. The data were collected in a German store over a period of 72 days during business hours, and over 18 million records of trips involving a cart or basket were collected. The results have been analysed using the two following steps. In Section 4.1, we give a general overview of shopper behaviour inside the store, with particular attention to each department, while in Section 4.2 we use the described technology to provide more detailed information about each shopper's path through the store, which can help retailers implement new cross-merchandising strategies.

4.1. General metrics

The experiment was conducted in a supermarket where a tracking system based on ultra-wideband technology allowed covering the entire area of the store. In particular, we analysed the shoppers' behaviour in 8 departments, which are shown and numbered in Fig. 1. The departments were defined by grouping categories in which similar products are sold. They are listed below.

1. Coffee, i.e. breakfast goods, coffee and tea
2. Dairy, i.e. dairy and refrigerated goods
3. Oils, i.e. oil, vinegar, and canned goods
4. Home, i.e. fabric and home care products
5. Frozen, i.e. frozen products
6. Cakes, i.e. cakes, cookies, and kitchen-ware
7. Drinks, i.e. alcoholic and soft drinks
8. Beauty, i.e. personal and beauty care.

An important metric that we consider first is the average number of visitors per store department. This metric gives managers information about the intensity of shopper traffic, and consequently it is important in defining the effectiveness of in-store marketing activities. In particular, if the retailer wants to improve in-store promotional or communication strategies, there is a need to know how the shopper moves and which areas are visited. This metric is also important in the design of the in-store layout and for generating impulse purchases (Sorensen et al., 2017). Recent studies on this topic have been carried out in order to identify general shopping patterns in terms of the store area covered on a shopping trip, such as: (1) the percentage of people visiting the whole store is very low, as confirmed by cart tracking studies that also document the extremely low occurrence of shopping trips that cover every aisle (Silberer et al., 2007; Sorensen, 2009); (2) the number of visited areas is inversely proportional to the size of the store (Hui et al., 2009). In line with these results, our target is to identify which areas of the store are the most excluded during a standard shopping trip and which are the most essential areas for the shopper.

The second metric we analyse is the average time spent in each department. As in (Sorensen et al., 2017), the amount of time spent inside the store has an important effect on the way the shopper moves and makes purchasing decisions. When retailers analyse shoppers' behaviour, for the purpose of implementing efficient marketing strategies, there is usually a focus on traffic. Traffic itself does not represent a proxy for purchases, but attention must be paid to traffic time because in this case traffic becomes shopping.

In this framework, our system is particularly relevant because it allows us to collect information about the number of people passing by each department (the number of carts, baskets transmitting signals by the tags) and at the same time detect their average stopping times. Therefore, the retailer can understand where the shoppers are spending their time, so as to make relevant offers directly where they are.

In this first part of the study, we present the average number of people passing by a defined area over the entire observation period. From Fig. 1(a and b) we can observe the distribution of people moving inside the store and their relative dwell times.

In the maps different colours identify the number of people that pass through each department, as well as the time spent in each department. As a first approximation, we assume that both variables are uniformly distributed over all the department's categories. As we can see in Fig. 1(a), one can immediately identify which are the ‘hot’ and ‘cold’ regions of the store in terms of the average number of people passing by each department per day. In our analysis, the most visited departments are ‘Cakes’, ‘Coffee’, and ‘Oils’. At first, a retailer can assume that the most popular products are in these departments and implement and evaluate new marketing strategies according to this information, without taking into account the layout of the supermarket. On the other hand, in order to differentiate transit areas from stopping areas, we need to consider dwell time. Thus, as shown in Fig. 1(b), the departments with the highest average spending times do not correspond with the ‘hottest’ departments in terms of traffic. People spent the most time in the following areas: ‘Frozen’, ‘Drinks’, ‘Beauty’, and ‘Oils’. In particular the average times spent in the different departments are as follows: ‘Coffee’ 69.6 s, ‘Cakes’ 85.73 s, ‘Home’ 97.5 s, ‘Drinks’ 112.23 s, ‘Beauty’ 115.49 s, ‘Oils’ 124.38 s, ‘Dairy’ 147.34 s, and ‘Frozen’ 179.08 s.

The distinction between transit time and stopping time becomes a key point for the in-store navigation analysis. As confirmed by different studies conducted by Sorensen Associates, 80% of a shopper's time is spent simply moving from one place to another and not looking at items for purchase. Also, a Wharton School study has confirmed that an high percentage of an individual shopper's time is spent moving around the store, and not directly in acquiring merchandise (Hui et al., 2009). Therefore, from a retailer's point of view, it is important to concentrate not just on the shopper who is hurrying past the department on their way to somewhere else, but mainly on shoppers who are spending more than a given amount of time there (Sorensen et al., 2012).

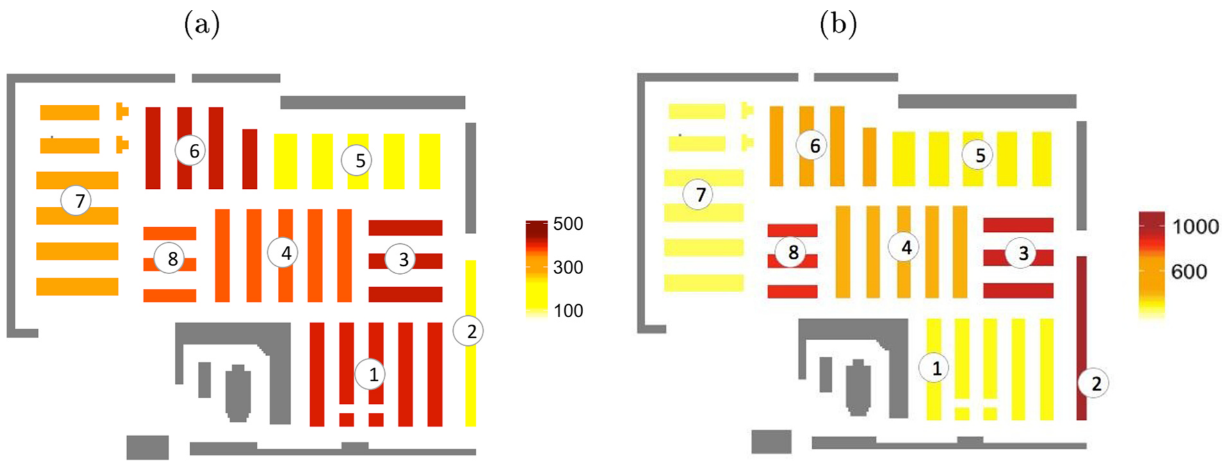

Fig. 1. (a)Density map, where the store's map colours are defined by the average number of people passing per day. (b) Time spent map, where the store's map colours are defined by the average dwell time. The actual values can be found in the colourbars next to the plots.

For this reason, we define a measure of the performance of a department in terms of reach and frequency, by multiplying the number of people passing by with the average time spent in that department. The Gross Rating Points (GRP) index has been developed by a professor at the Wharton School as a standard metric for advertising exposure in order to highlight the close relation between frequency and time (Fader and Lodish, 1990). In advertising, as well, GRP represents the total number of shopper seconds. Here, it is considered as an appropriate measure of the opportunity of a shopper to buy (or for a retailer to sell). According to this criterion, we can identify the most popular departments as 'Oils', where we observe a large number of people passing by (416) and a long average dwell time (125 s), while the least performing is 'Dairy', where a small number of people (143) with long stopping times (148 s) are found. The 'Coffee' department, where a large number of people (407) and a low average dwell time (69.6 s) have been observed, can be defined as a passing area, where most of the shopper flow is constrained, given its proximity to the entrance. From a marketing perspective, the combination of this information becomes important for retailers who want to actively understand their shoppers' needs and consequently make relevant offers for pushing through their purchases.

However, the output of this analysis is not aligned with other findings, according to which 'Dairy' is not a low performing area in supermarkets. However, that output could be misrepresented by the assumption that all the store's areas have the same size. To avoid this distortion, we consider a 'per meter' metric, which takes into account the different sizes of each department. In particular, the previous GRP index is normalized according to the area in square meters of each department:

$$GRPi = \frac{People_i * AVGt_i}{m^2} \tag{1}$$

Thus, as shown in Fig. 2, the departments with the highest GRP per square meter do not correspond with the highest departments in terms of GRP. For instance, 'Dairy' is the most frequented and visited area (it includes destination products and it is located at the side of the store, for logistics access) in line with what usually happens in most of the stores. As highlighted by Nielsen[1] fresh products are strong trip drivers, ranking highest among all food departments in terms of what drives the most trips to the store.

This analysis represents an important tool that retailers can use to take a step from passive to active retailing. While a passive retailer takes into account mainly gross measures, such as sales, margin, and

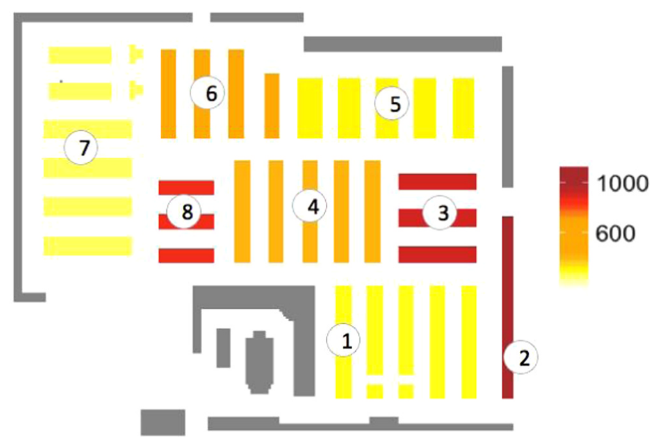

Fig. 2. the store's map colours are defined by the GRP per square meter index. The actual values can be found in the colourbars next to the plots.

space, to have a picture of the performance of the store, a more active retailer could use this information to make more efficient marketing strategies related to where the shopper is and to specifically where the shopper stops for longer. In this way, the retailer can guide the shopper and does not leave the shopper to find the products themselves. With this insight in mind, retailers have a better sense of where to focus their marketing efforts to drive additional visits. Thus, what happens inside the store has a strong impact on sales and the knowledge of how the shoppers navigate the store provides a great opportunity for making the store more profitable.

In contrast, a limitation of this analysis is the lack of a 'sales' metric. In this preliminary phase of our research, we do not have sales data to integrate with the traffic and time spent inside the store. As in (Sorensen, 2009), sales represent an important variable if compared with the shopping time. In particular, it would be very useful to know not only the sales per visit but the *seconds per dollar*. In fact, according to the principle by which the less time wasted for the shopper, the more sales will be made, shoppers spending money more quickly lead to greater overall sales. For this reason, the metric of 'Shopper seconds per dollar' used by Sorensen is one of the key measures of retailing success. Our technology allows integrating the tags and the sales data, so a future development of this study will certainly consider the 'sales' metric.

4.2. Path to purchase

The main goal of this section is to use the observational data in

[1] Understanding the impact of category shopping fundamentals, FMCG and Retail, 05/10/2016, Nielsen.

order to identify how the shoppers move around the store and to learn where they are (and where they are going), so as to build marketing strategies targeted to them. Our approach focuses on the analysis of the in-store shopping behaviour's fundamental pattern, which examines shopper movements through the store. Unlike the methods proposed in some previous publications (Page et al., 2018; Silberer et al., 2007; Hui et al., 2009; Larson et al., 2005; Moiseeva and Timmermans, 2010) we use the RTLS technology to identify the shopper journey inside the store. The collected information can be relevant for the retailers, who can accordingly improve both the shopping experience of their shoppers and the marketing, communication, and space design strategies, since the way shoppers move and interact with the environment is now accessible.

Considering the store layout, we made some assumptions about the possible shopper paths inside the store. In particular, we assumed that one person can go in and out of a department only by moving in a counter-clockwise direction, and also only between adjacent areas. In this way we built an Inbound/Outbound matrix, which is a double entry table reflecting the flow of people within the store for the entire period of observation. Each row records the average number of people entering each department. Each column records the average number of people exiting from one department. The entries and exits for each area are shown as the corresponding row and column of the matrix, so that all the interconnections between people passing each department are described explicitly and comprehensively.

The assumption at the base of our analysis could be considered very strong. In this particular study, we are working with static data, which gives us a picture of the in-store situation and does not allow a dynamic analysis of the cart's direction. We only know how many carts passed by an area and the average time they spent in the considered department. For this reason, an assumption according to which people can move only in a well-defined direction seemed to be necessary. According to the literature, the 'migration patterns' of shoppers throughout the store are highly correlated with the design of the store. The locations of the entrance and the exit largely define the shoppers' flow (Sommer and Aitkens, 1982; Larson et al., 2005; Groeppel-Klein and Bartmann, 2007; Sorensen, 2009; Hui et al., 2009; Kholod et al., 2011). As studied in depth by Sorensen and Associates, shoppers are used to coming in through a right entrance and making a counter-clockwise movement through the store. Moreover, they seem to be very resistant to changing this behaviour. Empirical studies have highlighted that the dominant shopper's traffic is around the store's perimeter in a counter-clockwise rotational pattern (Sorensen, 2003, 2009). The substantial majority of shoppers are right-handed, and tend to push their cart with the right hand, giving the cart a tendency to turn left, in a counter-clockwise direction. The aforementioned study used the PathTracker system, and was conducted in the United States. A similar study in the UK, Australia, and Japan, has highlighted that the in-store traffic patterns may be affected by the *vehicle traffic* patterns outside. So, in countries with a right-hand driving system, shoppers tend to move in a clock-wise pattern (Sorensen, 2009). Our analysis was conducted in Germany, where we considered it correct to apply the principle according to which consumers mainly move following a clockwise in-store pattern Table 1.

In order to identify the most probable paths within the store, we first defined a new variable, the outbound percentage, that quantifies how the flow splits from department a to the next department, b, by

$$OUT_{a,b} = \frac{P_{a,b}}{\sum P_a} \tag{2}$$

where $P_{a,b}$ is the number of people going from department a to department b and $\sum P_a$ is the total number of people that passed through department a. The value obtained for each department is listed in Table 2 in the form of a percentage.

Knowing the outbound percentage for each department, we can now estimate the conditional probability of each possible path inside the store. To do so, we first identify all possible paths, assuming that the shopper can move only between adjacent departments and only in the counter-clockwise direction (from entrance to exit), as we observed for most of the cases.

The probability that one shopper moves along one path is calculated as the conditional probability of moving in one area, given the probability that the shopper is has already moved to the adjacent one. Given $P(n-1)$ as the probability of passing through department *n-1*, we calculate $P(n)$ as the probability of moving into the next department n:

$$P(n) = \prod_{n=2}^{N} P(n|(n-1)) \tag{3}$$

where

$$P(n|(n-1)) = \frac{P(n-1)\bigcap P(n)}{P(n-1)} \tag{4}$$

Diagram Fig. 3 summarizes all 60 paths. A table listing the conditional probability of each path can be found in the Appendix (Table A1):

Fig. 4 shows the 10 most probable paths. We calculated that 44% of the people entering the store are going to move along one of them.

Knowing how the shopper moves through the supermarket and which area is visited, in particular in which order, is key information for possible marketing strategy. Namely, by identifying the shopper path one can objectively establish where the most efficient advertisement or secondary placement can be situated. In particular, the retailer can either direct the shopper to a less popular region or insert targeted offers of the next visited department based on the information acquired

Table 1
Inbound/Outbound matrix.

		inbound										
		IN	**Coffee**	**Dairy**	**Oils**	**Frozen**	**Home**	**Cakes**	**Drinks**	**Beauty**	**OUT**	**total**
outbound	**IN**		393	143			100					636
	Coffee				287		120					407
	Dairy		14		129							143
	Oils					135	151	130				416
	Frozen							135				135
	Home							200		122	49	371
	Cakes								290	112	63	465
	Drinks									137	153	290
	Beauty										371	371
	OUT											636
	total	636	407	143	416	135	371	465	290	371	636	

Table 2
Outbound percentage ($OUT_{a,b}$).

outbound	IN	Coffee	Dairy	Oils	Frozen	Home	Cakes	Drinks	Beauty	OUT	
IN		62%	22%			16%					**100%**
Coffee				71%		29%					**100%**
Dairy		10%		90%							**100%**
Oils					32%	36%	31%				**100%**
Frozen							100%				**100%**
Home							54%		33%	13%	**100%**
Cakes								62%	24%	14%	**100%**
Drinks									47%	53%	**100%**
Beauty										100%	**100%**
OUT											

by our shopper behaviour analysis.

This result is in agreement with the previous general metrics, where 'Oils' was identified as one of the most performing departments, even if 'Coffee' was the area most crossed. In fact, looking at the most probable paths, 9 out of 10 pass through 'Coffee' and only 7 out of 10 pass through 'Oils'. This confirms our assumption that 'Coffee' is just a passing area, through which a shopper is forced to pass, while 'Oils' is one of the most attractive areas, where the costumer chooses to go

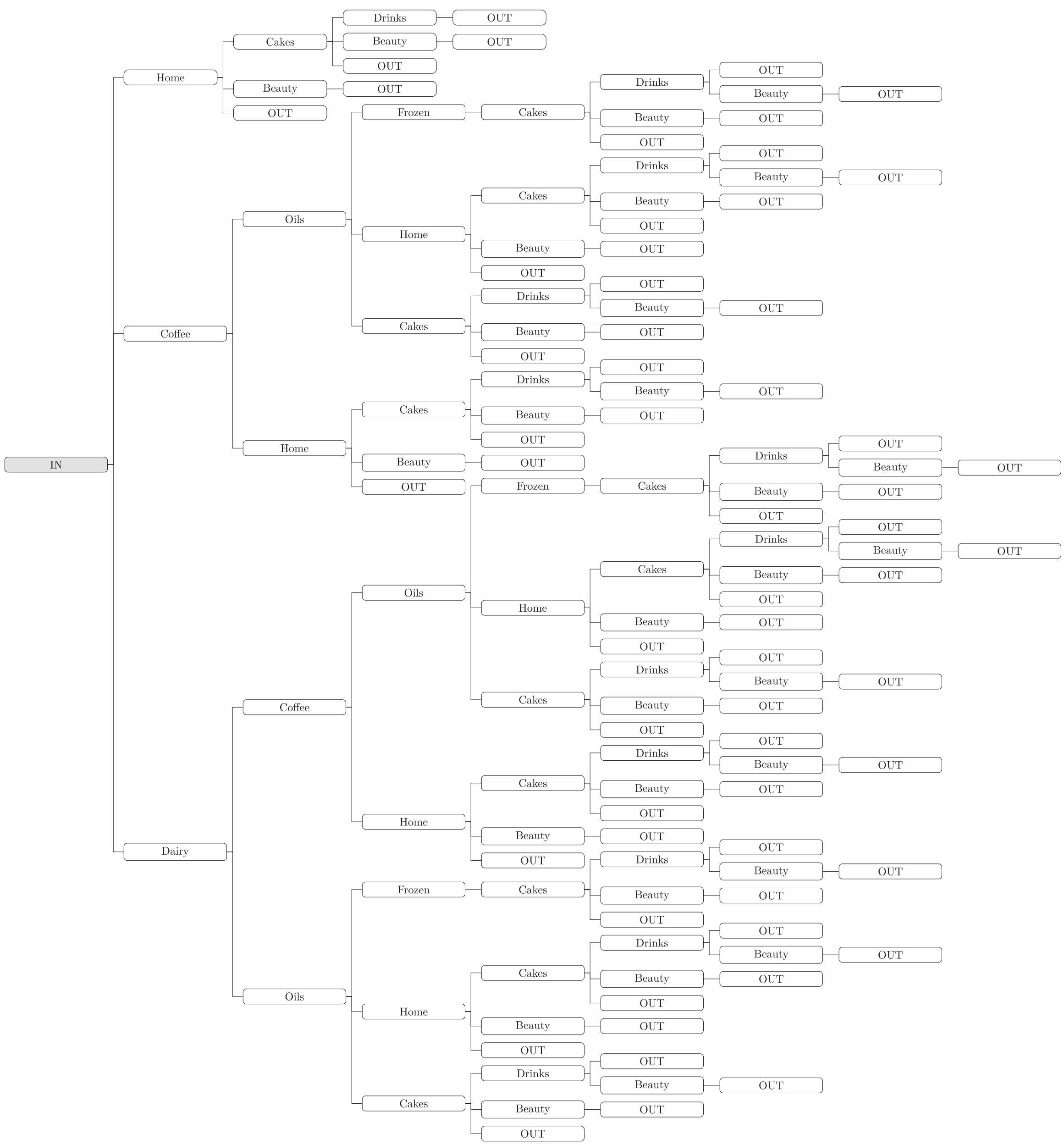

Fig. 3. Tree of Possible Paths.

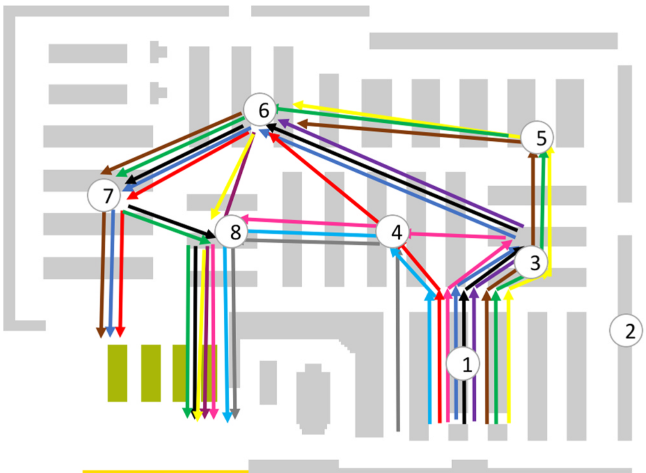

Fig. 4. Ten most visited paths in the store.

instead of other possible options ('Dairy' or 'Home').

These findings also have implications for the design of retail outlets, particularly they are useful information in understanding which layout changes are effective and under what conditions. The number of the area that shoppers will visit during shopping trips may be related to several circumstances, for example: (i) the time allotted by shoppers to the task, (ii) their need for only a few products, (iii) their expectations regarding how far they will walk on a shopping trip, etc.

Another key piece of information that we can extract from our analysis regards the relative frequency distribution of number of visited departments, where the percentage refers to the amount of shopping trips covering given number of departments over the total number of trips, as shown in Fig. 5.

Before discussing the results, we need to take in account a limitation of RTLS technology. First, trips that do not involve a cart or basket are not tracked; so shopping trips covering a small number of areas are likely to be under-represented. Second, shoppers were not tracked as they left their cart or basket to retrieve items from other areas of the store, possibly reducing measures of trips covering large number of areas. As first assumption, we consider that data from shopping carts and baskets provide a reasonable proxy for shopper behaviour (Sorensen et al., 2017), individual shoppers cannot be tracked easily and reliably and any post-hoc adjustments will be object of future studies.

From Fig. 5 we can obtain a first preliminary segmentation of shopping trips where main findings can be summarized as: (i) 29% of trips cover less than half of departments, in this particular scenario this means 3 or less departments, (ii) 60% of trips cover between half and three quarters of departments, i.e. from 4 to 5 departments, and (iii) 11% of trips cover more than three quarters of departments, i.e. it corresponds to more than 5 departments. In this context, Inman et al. have found a correlation between the number of visited departments (aisles) and the likelihood of unplanned purchases. They divided shoppers into three groups according to whether they visited 'all aisles', 'most aisles', or 'a few aisles' and reported that the group that visited 'all aisles' has the highest likelihood of making unplanned purchases, followed by the group who visited 'most aisles' (Inman et al., 2009). This result highlights that a decrease of trips covering only few departments shall correspond to an increase of unplanned purchases. Therefore, manufacturers and retailers should think strategically about driving the shopper through innovative department layout and shelf design in order to encourage them to visit as many departments and be exposed to as many product categories as possible.

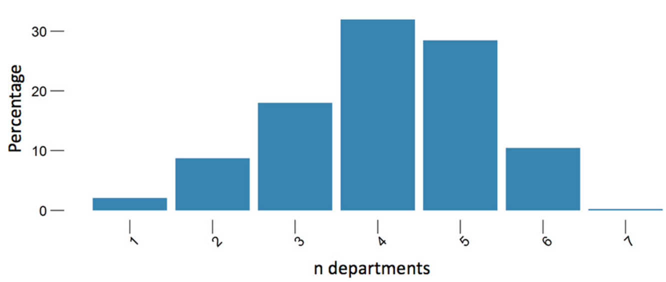

Fig. 5. relative frequency distribution of the no. of visited departments.

However in-store decisions are influenced by a broad spectrum of factors that are not taken into account in this preliminary classification and they result essential to cluster shoppers visiting the store in terms of shopping mission. *Shopping mission* is a categorization of shopping trips that involves the specific need states of shoppers entering the stores. The underlying consumption need is typically self-evident when it is related to short shopping trips that involve a limited number of items, commonly defined as being within a single product category. Other planned and major trips involve a lot of heterogeneous products, addressing assorted needs that are not so well-defined. Shopping missions are thus hard to identify, due to the in-congruent and nested relations between the multitude of product categories involved (Sarantopoulos et al., 2016). Numerous studies have analysed shopping behaviour by using empirical shopping trip data and found clear evidence for shopping trip segmentation based on time spent in the store, leading to different cluster configurations, for short, medium, and long trips (Larson et al., 2005; Sorensen, 2009) or based on nature of purchases behaviour (Kollat and Willett, 1967; Granbois, 1968). For example, according to a shopping mission segmentation outlined by (Sorensen, 2009) 'Quick' shoppers spend a short time in a small area, with relatively slow walking speed. This segment usually proceed to the checkout after only shopping a limited number of departments. Generally they satisfy well-defined and planned needs and spend their money a lot faster, so considering the *shopper seconds per dollar* as a measure of retailing success, these kinds of shoppers that spend their money more quickly lead to greater overall store sales (Sorensen, 2009). 'Fill-in' shoppers have a slightly faster walking speed and average spending speed while 'Stock-up' shoppers cover a large area, walk more quickly, but have a lower spending speed. The 'Stock-up' shoppers, given their major trips are more exposed to in-store stimuli and therefore can be easily influenced by promotions and advertisements. Retailers have to consider this important finding also considering that shoppers with 'Fill-in' mission, instead, are probably more difficult to be persuaded by marketing actions because of their attitude to shop. In fact, the percentage of unplanned purchases seems to be larger during 'Stock-up' shopping trips than during 'Fill-in' trips. This finding is justified by the exposure hypothesis, according to which during 'Fill-in' trips, the shoppers' needs are more clearly identified, so that they are less susceptible to in-store suggestion, whereas during 'Stock-up' trips, the shoppers' needs are not well defined and the shopper is more receptive to in-store stimuli. Furthermore, 'Fill-in' trips typically satisfy recurrent needs that are more urgent than most products purchased during 'Stock-up' trips. Therefore, 'Fill-in' trips probably involve less effort and less time commitments than 'Stock-up' trips, so that the measured purchase intentions deviate less from the actual purchase intentions (Kollat and Willett, 1967; Granbois, 1968).

Matching the diverse segments of shopping missions can help retailers in creating a variety of shopping experience addressing the distinctive need of shoppers' group since behaviour represents one of the most critical in-store factor. Departing from our preliminary segmentation, our future goal is to classify shopping trips in term of shopping missions integrating other factors such as time spent, travel distance, visited categories and preferred paths. By identifying distinctive missions, different target marketing strategies with personalized approach can be implemented.

5. Conclusions and future research

We see the retailing world as a dynamic environment where retailers have to continuously re-evaluate their strategies, test new ideas, eliminate worn-out actions, and revise those that work in the face of competitive reaction. For this purpose, having an automated system which collects a large amount of data represents the next step to having updated information of the shopper's behaviour throughout the different periods of the year. Furthermore, via our technology, we give retailers and producers the opportunity to verify if their marketing actions, such as promotions and advertisements, are successful, but also to identify new patterns in the shoppers' behaviour and anticipate new trends. In particular, via the application of RTLS technology in the retail environment, one can not only identify the most popular supermarket departments but also the most popular paths within the store, and consequently implement marketing and merchandising strategies ad hoc for the different areas of the store. Namely, it has been observed that a marketing strategy becomes more effective if it focuses on the shopper and less on the product (Sorensen et al., 2012).

In the first part of our analysis we analysed an index for the measurement of the attraction level of each department in terms of the average number of people visiting and the permanence time. Understanding which are transit areas and which are areas where a shopper stops longer provides a useful insight for retailers, who can then concentrate their marketing strategy exactly where the consumer is spending more time and consequently their attention rather than where the shopper is hurrying through the department looking for some other product. Knowing which are the key areas of the store in terms of frequency and stopping time helps the retailer focus their store marketing efforts on driving additional incremental visits, thus making the store more profitable.

In the second part of the analysis, we provided a novel method for estimating the probability of a path, by using a double entry table and a cumulative probability tree. The model is based on the categories of the states of dependence, where the probability of choosing a specific path is influenced by the path choices made earlier. By identifying the key areas of the store, the retailer can implement the right merchandising to influence travel to move in a particular direction and generate the best performance in terms of profits and sales.

The present work provides a starting point in studying shopping movement inside the store. It focuses on travel patterns without regard to purchasing behaviour. A study able to link travel and purchases may lead to an improved understanding of consumer motivations for purchasing certain items. Our system allows an integration of location system data with sell out data. Since the importance of providing this further information has been amply discussed in the literature, we want to introduce this metric in a future development of the current research. The combination of this complementary information could represent a big advantage for the retailer in better planning strategies, thanks to a solid awareness of their market, customers, and characteristics of the retail facilities.

Thanks to the RTLS system built around ultra-wideband technology we have been able to collect and analyse data that allows us to understand shoppers' behaviour without interfering with shoppers, thus making the results more trustworthy and experiments repeatable. The RTLS system presents a powerful tool in obtaining a large data-set by collecting a large amount of data. It allows observing shoppers' behaviour over a wide set of time periods, store formats, departments, and categories, allowing the creation of general and proved rules, norms, averages, and benchmarks to serve marketers, retailers, and researchers. Having a significant sample comprising a greater number of stores in different countries would be one of our main aims for further development of this study. Collecting data coming from different sources could provide insights into shoppers' in-store behaviour from a wider perspective, overriding single project goals. In particular, such a large amount of data could help researchers in creating a benchmark to assess shopping experience fundamentals: (1) comparing insights across different categories and store formats; (2) confirming (or not) some of the main behavioural science theories through data coming from actual shopper observation.

Finally, in this paper we have analysed static data on the purchase path process and we have presented some exploratory techniques useful for knowledge building and intuition. However, our system allows identifying the shopper trajectories inside the store and further investigation could be devoted to improving our analysis by clustering the trajectories acquired from shopping carts and baskets with the help of machine learning technologies. In particular, the possibility of obtaining information about the carts' flows could be very important in order to understand in which direction people move through the store. This information surely could help us in analysing more precisely the shopping path and allow us to identify the exact direction of the person. In this way we could improve our analysis by providing both the inbound and the outbound flow among categories without the need for formulating strong assumption constraining the directions of the movements. Furthermore, this innovative approach could help us obtain more punctual data and the retailer in improving and personalizing the shopping experience by better defining the different shoppers' missions.

Appendix A

See Table A1.

Table A1
possible paths to purchase ((%) probability to be passed through).

Coffee	Home	Beauty	OUT					5,99%
Coffee	Oils	Home	Beauty	OUT				5,20%
Home	Beauty	OUT						5,17%
Coffee	Oils	Frozen	Cakes	Drinks	OUT			4,65%
Coffee	Oils	Cakes	Drinks	OUT				4,48%
Coffee	Oils	Frozen	Cakes	Drinks	Beauty	OUT		4,17%
Coffee	Oils	Cakes	Drinks	Beauty	OUT			4,01%
Coffee	Oils	Frozen	Cakes	Beauty	OUT			3,41%
Coffee	Oils	Cakes	Beauty	OUT				3,28%
Coffee	Home	Cakes	Drinks	OUT				3,23%
Coffee	Home	Cakes	Drinks	Beauty	OUT			2,89%
Coffee	Oils	Home	Cakes	Drinks	OUT			2,81%
Home	Cakes	Drinks	OUT					2,79%
Coffee	Oils	Home	Cakes	Drinks	Beauty	OUT		2,51%
Home	Cakes	Drinks	Beauty	OUT				2,50%
Dairy	Oils	Home	Beauty	OUT				2,42%
Coffee	Home	OUT						2,41%
Coffee	Home	Cakes	Beauty	OUT				2,37%
Dairy	Oils	Frozen	Cakes	Drinks	OUT			2,17%
Coffee	Oils	Home	OUT					2,09%
Dairy	Oils	Cakes	Drinks	OUT				2,09%
Home	OUT							2,08%
Coffee	Oils	Home	Cakes	Beauty	OUT			2,05%
Home	Cakes	Beauty	OUT					2,04%
Dairy	Oils	Frozen	Cakes	Drinks	Beauty	OUT		1,94%
Coffee	Oils	Frozen	Cakes	OUT				1,92%
Dairy	Oils	Cakes	Drinks	Beauty	OUT			1,87%
Coffee	Oils	Cakes	OUT					1,84%
Dairy	Oils	Frozen	Cakes	Beauty	OUT			1,59%
Dairy	Oils	Cakes	Beauty	OUT				1,53%
Coffee	Home	Cakes	OUT					1,33%
Dairy	Oils	Home	Cakes	Drinks	OUT			1,31%
Dairy	Oils	Home	Cakes	Drinks	Beauty	OUT		1,17%
Coffee	Oils	Home	Cakes	OUT				1,16%
Home	Cakes	OUT						1,15%
Dairy	Oils	Home	OUT					0,97%
Dairy	Oils	Home	Cakes	Beauty	OUT			0,96%
Dairy	Oils	Frozen	Cakes	OUT				0,89%
Dairy	Oils	Cakes	OUT					0,86%
Dairy	Oils	Home	Cakes	OUT				0,54%
Dairy	Coffee	Home	Beauty	OUT				0,21%
Dairy	Coffee	Oils	Home	Beauty	OUT			0,19%
Dairy	Coffee	Oils	Frozen	Cakes	Drinks	OUT		0,17%
Dairy	Coffee	Oils	Cakes	Drinks	OUT			0,16%
Dairy	Coffee	Oils	Frozen	Cakes	Drinks	Beauty	OUT	0,15%
Dairy	Coffee	Oils	Cakes	Drinks	Beauty	OUT		0,14%
Dairy	Coffee	Oils	Frozen	Cakes	Beauty	OUT		0,12%
Dairy	Coffee	Oils	Cakes	Beauty	OUT			0,12%
Dairy	Coffee	Home	Cakes	Drinks	OUT			0,12%
Dairy	Coffee	Home	Cakes	Drinks	Beauty	OUT		0,10%
Dairy	Coffee	Oils	Home	Cakes	Drinks	OUT		0,10%
Dairy	Coffee	Oils	Home	Cakes	Drinks	Beauty	OUT	0,09%
Dairy	Coffee	Home	OUT					0,09%
Dairy	Coffee	Home	Cakes	Beauty	OUT			0,08%
Dairy	Coffee	Oils	Home	OUT				0,07%
Dairy	Coffee	Oils	Home	Cakes	Beauty	OUT		0,07%
Dairy	Coffee	Oils	Frozen	Cakes	OUT			0,07%
Dairy	Coffee	Oils	Cakes	OUT				0,07%
Dairy	Coffee	Home	Cakes	OUT				0,05%
Dairy	Coffee	Oils	Home	Cakes	OUT			0,04%

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