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Combining Sell-Out Data With Shopper Behaviour Data for Category Performance Measurement: The Role of Category Conversion Power

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Abstract:	Retailers need to manage a series of complex decisions relating to numerous products. To reduce this complexity, they have introduced category management practices, which consider groups of similar products (categories) that can be managed separately as single business units (SBUs). Although the concept that the store offer should be organised as a category mix and that this strategy allows for better overall store management is already consolidated, retailers still struggle to adopt an approach to the store performance measurement starting from a category level perspective. Nowadays, the available methods for measuring categories' performance are quite limited. The current trend sees the measurement of category performance mainly based on sell-out data that are ill-equipped to fully address category management issues. Retailers should broaden their field of analysis not only by focusing on the product/sales perspective but also by including other methodologies such as shopper behaviour analysis. In this regard, the use of technology offers the retail sector new perspectives for those analysis. Therefore, we intend to contribute to the ongoing debate on the retail analytics topic by presenting a shopper behaviour analytics system for category management performance monitoring. More in detail, we could derive a new key performance indicator, category conversion power (CCP), aimed at analysing and comparing the single categories organised within the store. The research is based on a unique dataset obtained from a real-time locating system (RTLS), which allowed us to collect behavioural data togheter with sell-out data (from POS scanner). We argue that retailers could exploit this new analytical method to gain more understanding at the category level and therefore make data-driven decisions aimed at improving performance at the store level.
Suggested Reviewers:	
Opposed Reviewers:	
Response to Reviewers:	

Dear Prof. Harry Timmermans,

We would like to thank you and the reviewers for reviewing the manuscript again for the second stage of the review process.

We have revised our manuscript further, according the new suggestions coming from the Reviewers #1 and #3.
We hope that you will be satisfied with the further amendments which we have made to the manuscript after taking on board the feedback.
We thank you for considering our revised manuscript for publication and look forward to receiving your kind response.

Best regards

Response to Reviewer #1

Reviewer #1: Thanks to the author/s for nicely addressing the issues raised from the reviewers. However, still I have some queries as below:
1. Considering the sell-out data (only) is not sufficient to measure the category performance measurement. Author can incorporate some other determinants to strengthen their study.

Response: *We appreciate your effort and attention in evaluating our paper and we thank the reviewer for his/her positive feedback that allowed us to improve the quality of the paper.*
In fact, this was the premise that prompted our work to develop: sell-out data are taken into consideration in relation to some variables of shopper behaviour, such as purchase time and purchase path made. We believe that other variables may be introduced in future works thanks to the development of more complex machine learning algorithms that will also allow the identification of other aspects such as age, gender and sentiment of the shopper.

2. In what extent, this approach (sell-out data and shopper's behaviour vs category performance measurement) is better than the exiting approaches should be presented to prove this study promising.

Response: We thank the reviewer, in this case, the practical implication section was substantially improved focusing on a stronger emphasizing on such concept.

Response to Reviewer #3

Reviewer #3: It has been found that the relationship between the behavioural aspects and parameters establishing synergy among the category sellers along with its impact on conversion has well elaborated by the author, the significance of big data to frame category mix and consumer preference relationship/ strategy has been effectively balanced by the author. But how category conversion power directly influence the purchase intension of the customers and on what basis technological aspects (data collected with the help of POP) represent the actual correlation between Physical sales and mind set of customers still need to be work out . Over all the contents are well designed.

Response: *We are pleased that our responses have now clarified most of the previous remarks. As for the remaining ones, we have now addressed them by further strengthening the section on limitations and directions for future research.*

Combining Sell-Out Data With Shopper Behaviour Data for Category Performance Measurement: The Role of Category Conversion Power

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Abstract

Retailers need to manage a series of complex decisions relating to numerous products. To reduce this complexity, they have introduced category management practices, which consider groups of similar products (categories) that can be managed separately as single business units (SBUs). Although the concept that the store offer should be organised as a category mix and that this strategy allows for better overall store management is already consolidated, retailers still struggle to adopt an approach to the store performance measurement starting from a category level perspective. Nowadays, the available methods for measuring categories' performance are quite limited. The current trend sees the measurement of category performance mainly based on sell-out data that are ill-equipped to fully address category management issues. Retailers should broaden their field of analysis not only by focusing on the product/sales perspective but also by including other methodologies such as shopper behaviour analysis. In this regard, the use of technology offers the retail sector new perspectives for those analysis. Therefore, we intend to contribute to the ongoing debate on the retail analytics topic by presenting a shopper behaviour analytics system for category management performance monitoring. More in detail, we could derive a new key performance indicator, category conversion power (CCP), aimed at analysing and comparing the single categories organised within the store. The research is based on a unique dataset obtained from a real-time locating system (RTLS), which allowed us to collect behavioural data togheter with sell-out data (from POS scanner). We argue that retailers could exploit this new analytical method to gain more understanding at the category level and therefore make data-driven decisions aimed at improving performance at the store level.

Keywords: Category management, Performance Measurement, Shopper behavior, Retail marketing, RTLS technology, Big Data

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1. Introduction

The retail landscape has greatly changed during the last few years—in terms of consumers' behaviours, new forms of competition and technologies. One of the most enduring trends is the growing breadth and depth of assortments, following the growing sophistication and differentiation of consumer demand. This poses new challenges for retailers who need to manage a series of more complex decisions. To reduce this complexity, they introduced category management practices. Category management (CM) entails considering a group of similar products as a single business unit (category), which can be managed separately from others Nielsen (1992). The importance of CM is well recognised by both practitioners (ECR, 2020) and academics Voleti et al. (2017), Gooner et al. (2011). It has played a germane role in the evolution of retail marketing since its introduction in the late 1980s; however, as the retail landscape has changed a lot, some evolution in CM practices is also needed. Generating insights into consumer shopping behaviour and the shopper journey is becoming increasingly strategic to develop and implement superior category solutions and win competition with a differentiated shopping experience (ECR, 2020). Hence, a relevant issue is the performance measurement of categories. Retailers still struggle to adopt an approach to store performance measurement starting from a category level perspective. Traditionally, they rely on sales data to measure category performance. However, as stated by Desrochers and Nelson (2006), sales data are ill-equipped to fully address CM issues. For example, if an item has been concurrently sorted into more than one category, scanner data cannot identify from which category a sale was made. Moreover, sales data cannot show whether the product performance regarding revenues depends on the shelf position (shelf planogram), the category position inside the store (store layout), the product availability (stock level), etc. Definitely, sell-out data cannot explain category performance if not supported by other information related to in-store shoppers' behaviour. To face these measurement issues, retailers should broaden their field of analysis by focusing on other sources and types of data than product sales, such as shopper behaviour analysis Ferracuti et al. (2019). Combined with scanner data, these could offer vital insights to implement CM more effectively. Shopper behaviour analysis can benefit greatly from the new opportunities offered by technological advances Grewal et al. (2018), Ferracuti et al. (2019), Kaur et al. (2020). Some of the most relevant studies explore technology as a possible 'bridge' between the online and offline dimensions, useful for analysing and understanding in-store purchasing behaviours Schnack et al. (2021) , Aw et al. (2021). Data on customers' browsing ('path data') and purchase ('intent to buy' by adding to cart, abandoning the cart, etc.) behaviours that were once available only to online retailers are now being integrated into physical stores Boone et al. (2019), thanks to new in-store technologies. Traffic counters, infrared sensors, and video cameras can now track customer traffic and paths through the store, generating a lot of in-store data related to customer behaviour. Combining 'new' and 'old' sources of data, nowadays 'retailing is at the centre of a storm of big data opportunities and challenges', which calls for more research on how to derive value from them (Dekimpe, 2020). Retailers are seeking means to exploit the huge amount of collected shopper data (e.g. what they purchase, how they move in the stores, etc.) to extract valuable knowledge that facilitates effective decisions. However, more research is needed to objectively document the advantages of adopting a (big) data-driven approach. Based on these premises, our research fits at the crossroads of two research streams—the effective measurement of categories' performance and the effective use of big data to generate insights into shopping behaviours—and our scope is brick-and-mortar retail environments. Accordingly, the aims of this study are twofold:

1. To introduce a more effective CM scorecard of indicators.
2. To objectively demonstrate the usefulness of big data for retailers' strategies and how to extract value from them.

In particular, we propose a new key performance indicator—category conversion power (CCP)—which combines sell-out data with behavioural data, answering the recent call of Ferracuti et al. (2019). Starting from that, we argue that retailers could get a more comprehensive understanding of the performance at the category level and therefore make data-driven decisions aimed at improving the performance at the store level. Following the above discussion, the rest of the paper is structured as follows: Sections 2 and 3 review the relevant literature and research design, respectively; Section 4 describes the methods; Section 5 outlines the main results; and Sections 6 and 7 discuss the implications and conclusions, respectively.

2. CM in retail: The category performance measurement issue

In searching for new ways to improve the store's competitiveness and performance, CM is one of the most challenging marketing tasks for retailers Hübner (2011) Hübner and Kuhn (2012). Approaching CM means for manufacturers and retailers to change their focus from individual brands to overall product category performances Desrochers and Nelson (2006). According to Blattberg and Fox (1995), a category is a distinct, manageable group of products that consumers perceive to be related and/or substitutable in meeting a consumer need. Thus, CM means managing categories as strategic business units Dupre and Gruen (2004). As a pillar of efficient consumer response (ECR) practices, CM is aimed at supporting retailers in providing the right mix of products, the right price, with the right promotions, at the right time, and at the right place Gruen and Shah (2000). Several studies have examined and confirmed the positive impact of CM practices on store performance Gooner et al. (2011), Dupre and Gruen (2004), Basuroy et al. (2001) , Dhar et al. (2001), Gruen and Shah (2000), Zenor (1994). Although the topic has been studied from different perspectives, a common vision emerges: the authors agree that there is a need to plan, implement, and measure categories as single entities to optimise their coordination within the store. In considering CM as a strategic process Blattberg and Fox (1995), the category performance measurement is a critical activity. Knowing the category performance may be useful to assortment planning, define promotional programmes involving related categories, understand the best position for merchandise material, and study store layouts' performance, etc. Furthermore, the need for a scorecard of indicators for the CM was already exposed in 1995 by the CM Subcommittee of the ECR Best Practices Operating Committee and the Partnering Group

Inc. Until now, the most common methods have been based on sales data. Scanner data are employed for different purposes: to understand interrelation among different stock keeping units (SKUs) to group highly interrelated products into categories, such as milk, cream, and butter in the 'Dairy category' Nielsen (1992), Gooner et al. (2011); to identify cross-category interrelations to provide powerful pieces of information in the process of understanding and managing the retailer's business Tanusondjaja A (2016), Hruschka H (2011), Srinivasan S (2011), Seetharaman P B (2005), Russell G J (2000), etc. Following the same perspective, Musalem et al. Musalem et al. (2018) used shopping basket data (products sold, units sold, date, and time for each purchase recorded in a single month from a mid-sized supermarket in Latin America) to detect interrelations among product categories. However, retailers still struggle to adopt a set of indicators at the category level, which integrates different data other than scanner based one. According to Desrochers and Nelson Desrochers and Nelson (2006), sales data are ill-equipped to fully address CM issues, and they need to be integrated with other information related to in-store shoppers' behaviour to provide a full category performance understanding. The CM process can be improved by adding consumer behaviour insights to traditional point-of-purchase scanner information. In this way, manufacturers and retailers can answer a set of strategic questions, such as 'how much space to allocate to each category?', 'where to place each category?' or 'how does each category perform?'. In this context, technology, particularly big data analytics, can play a great role in enabling new CM decision support systems (ECR, 2020) Hübner (2011).

3. The 'empirical science' of in-store shopper behaviour

Understanding shopper behaviour is one of the keys to success for retailers, and shopper behaviour metrics are imperative in the retail industry due to their direct influence on performance indicators Phua et al. (2015). Answering questions—such as which retail attributes are important to which shoppers and how shoppers behave within different store formats and shelf layouts—provides powerful insights for manufacturers and retailers who want to improve the in-store shopping experience Ferracuti et al. (2019). Research on shopping behaviour has a long tradition, and various issues have been investigated over years. Many studies focused on the relative importance of in-store features, such as retail atmosphere and smell Chebat et al. (2000), Yalch and Spangenberg (2000), Solomon (2010); colour McKenna (2020), Guild and Wilhide (1992); music Morrison et al. (2011), Solomon (2010); merchandise Baker et al. (1994); moods, layout, signage, fixtures, and fittings Newman et al. (1996), etc. Also, the relevance of in-store advertising is being increasingly recognised Schneider and Rau (2009), Harris (2009). From a methodological standpoint, different methodologies have been implemented, ranging from conventional methods (such as surveys) to laboratory or field experiments. It is well recognised that natural observation of shoppers in-store offers some unique advantages compared to laboratory experiments or shoppers' self-reports Sorensen et al. (2017), which are based on customer's retrospective recall. Procedures for tracking in-store shopper behaviour appeared in the marketing literature during the 1960s Granbois (1968) and were conducted mainly by manual observation of the researcher at the point of sale. More recently, technological advances have offered new tracking tools, such as radio frequency identification (RFID) tags attached to baskets/shopping carts, Bluetooth through mobile phones Phua et al. (2015), and video observation. They allow data collection in an unobtrusive, real-time, and inexpensive way Landmark and Sjøbakk (2017). These procedures were foundational to the 'empirical science' of shopper behaviour Larsen et al. (2020), Seiler and Pinna (2017). Therefore, new sources of in-store data related to customer behaviour have emerged: traffic data—related to the number of shoppers entering the store, and path data—related to the subsequent interactions with various store elements before making a purchase decision. For example, Kanda et al. Kanda et al. (2008) tracked shoppers' trajectories with sensors to predict shoppers' future behaviours. Hui et al. S Hui (2009) used data collected through RFID tags to verify the behavioural hypothesis on customers' purchase processes. Moreover, Sorensen et al. Sorensen et al. (2017) and Landmark and SjØbakk Landmark and Sjøbakk (2017) adopted the RFID system to conduct an analysis on shopping patterns in retail stores. Lu et al. Lu et al. (2013) measured the effect of queues on customer purchases using data on a queuing system (collected via video recognition technology) combined with point-of-sales data. Ferracuti et al. Ferracuti et al. (2019) applied a real-time locating system (RTLS) to detect shopping paths and provide preliminary shopping trip segmentation. Although a growing interest in using these technologies in retail is noteworthy, the analyses conducted by the aforementioned studies have produced outputs, mainly at the store level. In this work, we intend to contribute to the existing literature by providing insights at the single category level. Hence, if it is true that CM is necessary for performance improvement at the store level Gooner et al. (2011), Dupre and Gruen (2004), it is equally fundamental to introduce methodologies that examine performance at the category level and allow a comparison among them Musalem et al. (2018).

4. The 'storm' of big data

The new sensors and tracking systems represent new sources of data that contribute to the phenomenon of big data in retailing, thanks to technological advancements. Nowadays, retailers can integrate different data sources Bradlow et al. (2017): CRM and POS systems, credit cards or loyalty cards, email, in-store visits, web logs, social media data, etc. They may use big data for several purposes, including consumer trend analysis, future demand forecasting, understanding consumer needs and motivations, improving cross-selling, enhancing pricing, offering customised product recommendations, implementing market segmentation, etc. Large volumes of unstructured and structured data from various sources contain valuable insights into customer behaviour, which could contribute to the growth of retail businesses. Considering this transformation, data are changing into something that is much more dynamic and fluid, generated daily through various consumer interactions. The rapid growth in consumer-generated big data—which are mostly sourced from various types of mobile devices and sensor technologies—has created new challenges for retailers in leveraging such data within their decision-making practices. Retailers are still struggling to exploit the huge amount of collected customer data (e.g. what they purchase, how they move in the stores, etc.) for extracting valuable knowledge that facilitates effective decisions.

Consequently, there is a growing need to address questions on how to make sense of these vast amounts of raw information, answering the so-called 'big data gap' Aversa et al. (2021).

5. Research design

5.1. The technology

To collect shopper behaviour data, we decided to use an RTLS based on ultrawide band (UWB) technology applied in a real-world German supermarket. As already demonstrated by Ferracuti et al. Ferracuti et al. (2019), RTLS is a suitable and profitable technology for indoor location purposes M Paolanti (2017), Contigiani M (2016), Sturari M (2016). The three phases that concerned the RTLS tracking and the successive creation of the dataset were as follows:

1. Monitoring the in-store shopper path through tags and anchors; tags were integrated with the shopping carts and baskets for tracking the path and sending data to the anchors; anchors are the antennas installed in the ceiling of the store to form a homogeneous grid that covers it entirely; they collect data from the tags and forward them to the RTLS server;
2. Sending the data collected by the RTLS to a cloud server;
3. Processing and storing data in a database. During this phase, the system filters eventual noise and anomalies based on the following two hypotheses: the first is that the points with an attraction time of less than five seconds are filtered since it is too short for the trajectories crossed in less than two minutes; the second is that for a basket or cart stopped for more than five minutes, we consider a novel trajectory since it is assumed that it is taken by another buyer.

5.2. Experiment: Context and methodological choices

The experiment was conducted in a German supermarket during business hours for three weeks (from 08/28/017 to 08/16/2017, according to the sell-out data received from the store), i.e. 18 days (considering that on Sunday the store is closed). We analysed shoppers' behaviour in 10 categories, which are shown and numbered in Figure 1.

The following categories were defined by grouping departments in which highly interrelated products Nielsen (1992), Gooner et al. (2011) were sold:

- Packaged Food
- Fabric and Home care
- Pet food
- Personal Beauty care
- Soft drinks
- Spirits

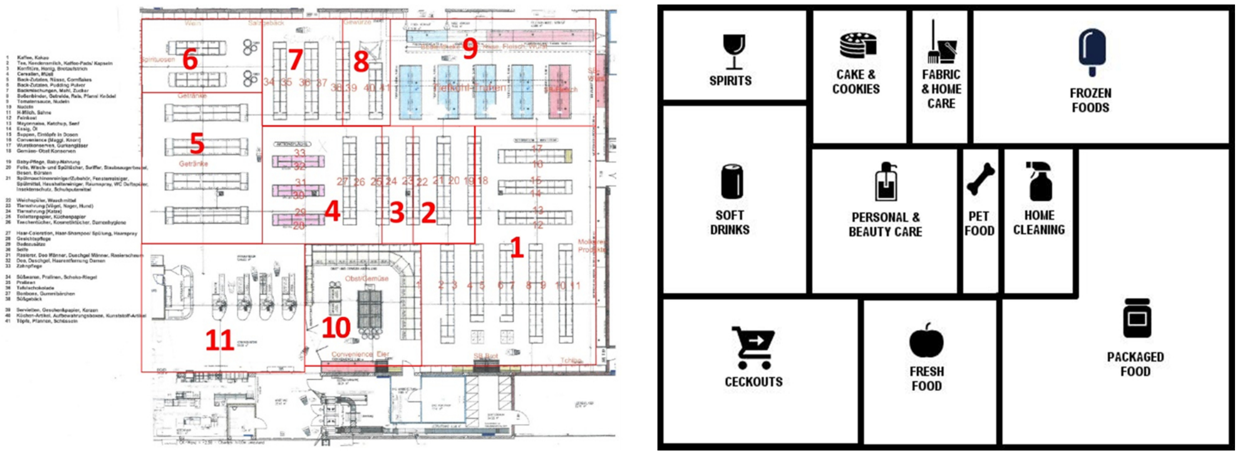

Figure 1: Store layout (left) and categories (right)

- Cakes and cookies
- Home cleaning accessories
- Fresh food
- Frozen food

To analyse the categories, the store layout has been ideally divided into a grid to determine each basket and cart exact position. Each cell of the grid corresponds to a real store area measuring 20 cm 20 cm. The RTLS allows us to count exactly how many carts and baskets that passed on each cell (area of the store), the relative stay time, and to recreate the exact shopper path inside the store, aggregating cells where the cart/basket passed. Also, it is possible to determine exactly the 'walkable metres' in reference to both the store and each category, defined as the sum of the cells where there is no structural store element (shelves, walls, displays, check-out, etc.), which prevents the shoppers' passage, thanks to this system. Finally, we selected the areas corresponding to categories on the store layout and plan and obtained the 'coordinates' needed to extract for each category the relevant data from the database. Once the category area was defined through the relative coordinates, it was possible to extract the total passing carts/baskets in that area in a specific period, the average stay time, and the distance travelled by the carts/baskets in that area, obtaining a full overview of each category traffic flow. The RTLS tags are linked to carts/baskets and not to a single person; this means that each time a cart/basket enters a specific area, the system counts a new passing, regardless of the person holding the cart/basket. Considering this, for the data extraction phase, it was decided to include the corridors adjacent to the categories in the coordinates of each area. In this way, we avoided counting twice a shopper entering a category from the corridor, then going out from that same corridor, and entering the category again. In Figure 2, we represent the subdivision of the store into the category areas, resulting from the process previously illustrated (picture 'a': in blue store walls, shelves, and displays, in orange store check-out, in green store entrance), the category borders (picture 'b'), and the resulting category areas (picture 'c').

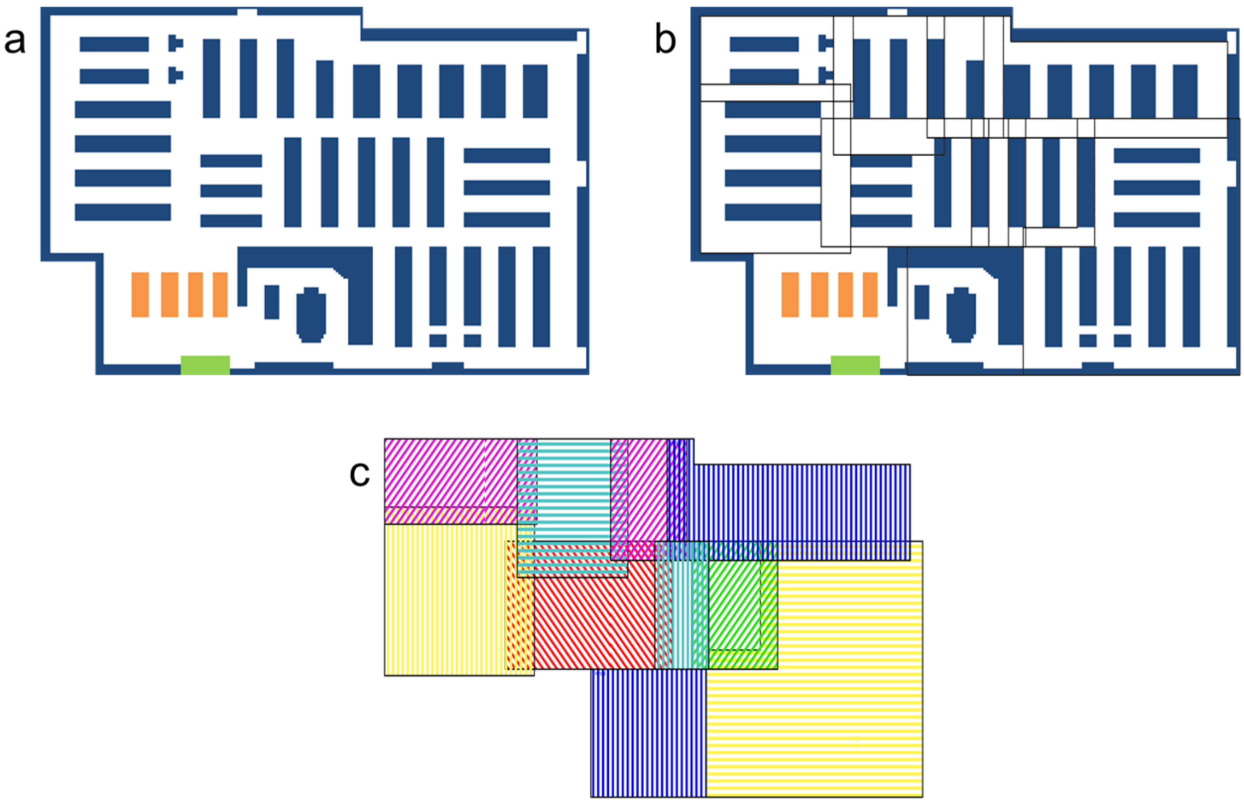

Figure 2: Store subdivision into category areas

6. Main findings

Table 1 shows the sell-out data and behavioural data obtained by the RTLS for each category.

SECTOR	PASSING	AVG DISTANCE	AVG SECTOR DWELL TIME	WALKABLE METERS	TOT Volume (Packs)	TOT Volume (L/kg)	TOT Value (EUR)
PACKAGED FOOD	12.723	36,46	03:04	241,96	51.412,12	20.342,26	86.777,46
FABRIC AND HOME CARE	9.912	6,55	00:20	48,72	3.473,85	2.151,85	8.233,38
PET FOOD	5.697	4,92	00:14	29,28	6.048,63	1.735,74	5.461,87
PERSONAL BEAUTY CARE	12.008	12,74	00:51	121,68	6.292,79	806,66	13.967,95
SOFT DRINKS	12.162	14,60	01:25	142,84	13.059,97	24.888,05	18.917,33
SPIRITS	3.776	11,79	00:35	82,88	5.943,48	4.668,91	18.217,70
CAKES AND COOKIES	8.885	11,86	00:43	84,64	15.935,43	2.801,01	22.619,59
HOME CLEANING ACCESSORIES	6.670	9,15	00:31	52,76	1.486,70	119,71	2.535,42
FROZEN FOOD	12.715	15,37	01:32	132,48	61.796,24	22.412,17	93.846,70
FRESH FOOD	8.585	18,24	01:31	54,32	10.845,90	5.597,53	19.566,15

Table 1: Sell-out and behavioural data for each category

Based on these data, we proposed a variation in the gross rating point (GRP_i) index, already developed by Ferracuti et al. (2019). They defined GRP_i as a measure of the category performance in terms of reach and frequency by multiplying the number of people passing by with the average time spent in each department of the store; this index was then normalised considering the size of each department, inducing the following formula: $GRP_i =$ (Peoplei AVGti)/m2. To better describe the way in which shoppers navigate the category, we proposed to use the previously defined 'walkable metres' in place of 'total area' of the category because the former represents the actual category area where shoppers can walk through. In this way, the previous GRP_i is calculated as follows: $GRP_i =$ (Passing AVG sector dwell time)/walkable meters.

7. The CCP Index: A New KPI

As already said, the GRP_i provides a measure of performance in terms of reach and frequency: the bigger GRP_i is, the more the category is visited by a greater flow of shoppers and for a longer period. It could therefore be assumed that a category with a high GRP_i is a store area that has high potential regarding the number of shoppers and exposure time. For the German supermarket we analysed, the fresh food category was the category with the highest GRP_i (Table 2).

Nr	**Category**	GRP_i
1	Fresh food	14382.09
2	Packaged food	9675.29
3	Frozen food	8829.86
4	Soft drinks	7237.26
5	Personal beauty care	5032.94
6	Cakes & cookies	4513.88
7	Fabric & home care	4068.97
8	Home cleaning accessories	3919.07
9	Pet food	2723.98
10	**Spirits**	**1594.59**

Table 2: $GRP_i =$ Passing AVGti sector dwell time / walkable meters (m2)

Table 3 Ranking of categories based on sell-out data.

Comparing the value of GRP_i to the sell-out data for each category, retailers could measure the impact of the current strategy of the category and understand which categories need a change. For example, while the 'Fresh food' and 'Packaged food' categories ranked the top positions in both rankings, the 'Fabric home care', 'Home cleaning accessories', and 'Pet food' categories were the least performing, ranking the last positions in both index. However, there are some categories that showed a performance hard to understand because they have a good position in a ranking and a poor one in the other. To solve this dilemma, we introduced the 'CCP' index, defined as follows: CCPi = (Total value of category)/GRP_i. Using this new index helps in comparing the sell-out data of different categories, which are normalised regarding the potential for shopper traffic (passing and stay time) within each category, expressed by GRP_i. Table 4 presents a novel category ranking based on the CCP

Nr	Category	TOT (Euro)
1	Frozen food	93846.70
2	Packaged food	86777.46
3	Cake & cookies	22619.59
4	Fresh food	19566.15
5	Soft drinks	18917.33
6	**Spirits**	**18217.70**
7	Personal beauty care	13967.95
8	Fabric & home care	8233.38
9	Pet food	5461.87
10	Home cleaning accessories	2535.42

Table 3: sell-out of each category

index: when the index presents relatively high values, it means that the category is strong in converting traffic flow in sales. However, when the CCP index presents a low value, it means that the category cannot convert the high traffic into purchases.

Nr	Category	CCP
1	**Spirits**	**11.42**
2	Frozen food	10.63
3	Packaged food	8.97
4	Cake & cookies	5.01
5	Personal beauty care	2.78
6	Soft drinks	2.61
7	Fabric & home care	2.02
8	Pet food	2.01
9	Fresh food	1.36
10	Home cleaning accessories	0.65

Table 4: CCP of each category

8. The CCP scorecard

To understand how the CCP index is determined by the different categories' sell-out performances, especially when categories have the same potential traffic flow, we used 'data visualisation', associating the CCP value of each category with the corresponding turnover. In this way, we can obtain a scorecard where each category can be considered a 'strategic business unit', which is useful for formulating category management strategies. In Figure **??**, we illustrate our CCP scorecard based on two dimensions: the total value (sell-out, Euro) and the CCP of each category.

The scorecard based on the CCP (Figure 3) aims to identify the actual ability of each category to perform within the store, allowing professionals to make more effective strate-

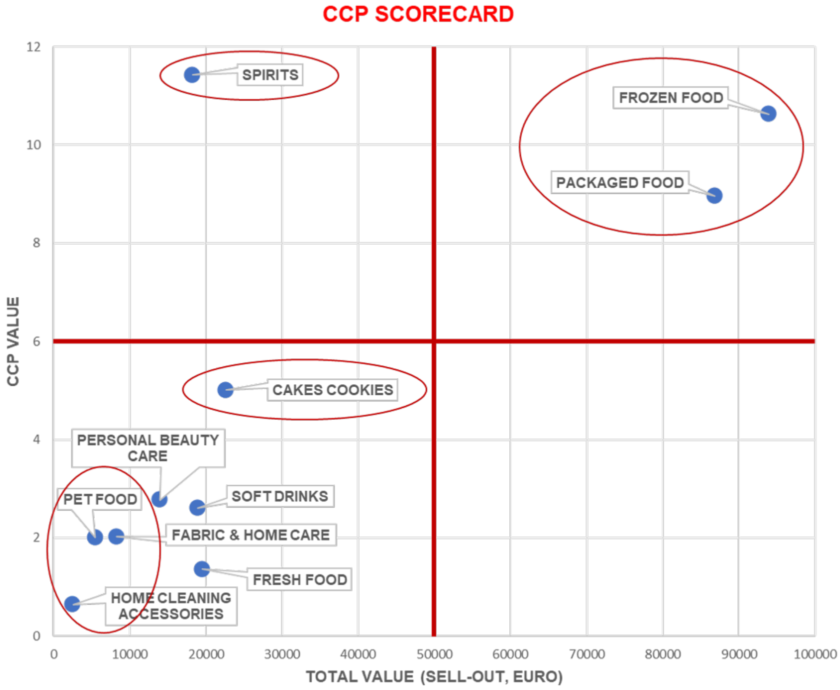

Figure 3: CCP scorecard

gic category management decisions. Considering the results illustrated in Figure 3, the 'Frozen Food' and 'Packaged Food' categories are the best-performing categories—those characterised by high sell-out and high CCP values. These are the less problematic categories because they can convert the high potential in terms of traffic in sell-out. Therefore, managers should continue to invest in these categories, capitalising on their high 'power' to convert traffic into sales (high CCP value). The categories 'Fabric home care', 'Home cleaning accessories', and 'Pet food' are the worst—those characterised by low values in both indicators. Considering their low ability to convert traffic into sell-out, managers could decide, for example, to move these categories towards the less strategic and low performance store areas, modifying the store layout. Above all, the scorecard allows professionals to better understand and manage the categories with low sell-out in absolute value but good (or excellent) performance in terms of CCP, such as the 'Spirits' category; considering the not-bad potential to convert traffic, managers could increase the number of shoppers visiting this category and/or the stay time to increase sell-out 'Spirits'. Looking only at the sell-out data and traffic data (GRP_i), managers may be led to think of disinvesting from this category; however, the CCP index is the highest, showing the very high potential of this category to convert the shopper flow into turnover. Hence, it could be considered a strategic category, and it could be very convenient to invest in some store marketing initiatives to increase the traffic flow and/or the time spent in category. 'Spirit' proved to be the category with the greatest conversion power but with a potential in terms of traffic flow still unexpressed compared to the average store potential. In this analysis, the necessity of an increase in the number of shoppers and in the stay time to obtain a given increase in sell-out was unexplored. Future studies are required in this sense. In any case, to determine which of the two strategies induces a greater increase in turnover, a category manager could test different category strategies, aiming to increase the traffic flow in the category (for example, through cross-promotions with other categories or by placing promotional material in the categories with the highest traffic to convey a greater flow in the category) and to increase the time spent in the category (for example, by placing communication merchandising material in category, such as free-standing display units, shelf edging, digital signage, posters, banners, etc.). It should not be surprising that there are no categories in the fourth matrix quadrant—those with high turnover in the presence of a low CCP—and that it is closely related to the CCP formulation. Indeed, the CCP is calculated by comparing the category sell-out volume with the GRP_i value, an expression of the category traffic volume. Therefore, for a low CCP value, there should be low sales performance compared to other store categories. If the sales and traffic volumes were equally high, we would have an average CCP value, as in low traffic volume and low sales performance. However, if the sales performance was high with low traffic, we would get a maximum CCP value (as for 'spirit' category). Therefore, the condition to obtain a low CCP value is necessarily the concomitant presence of high traffic volumes with poor sales performance or high sales performance but with a traffic volume (which is the denominator) tremendously higher than other categories (which is of course possible from a theoretical viewpoint, but improbable in reality, or related to an extremely specific situation). Obviously, it is necessary to talk about low, high, and medium performances of traffic or sales in a relative way by comparing the categories with each other within the same store over the same period.

9. Conclusions

Retailing is one of the largest industries in the world and plays a central role in all countries' economy. In Europe, even when limiting oneself to grocery retailing, sales forecasts reach 2289 billion euros by 2022 (IGD, 2018), with millions of people employed in the sector. Given its size and ubiquity, research aimed to contribute to solving the challenges that retail is facing can benefit many stakeholders (Dekimpe, 2020) and counteract the 'Retail apocalypse', that is, the mass closures of many bricks-and-mortar retail stores, particularly in the United States (Peterson, 2017), partially due to the rise in online sales. Our work goes in this direction, showing how the opportunities of technology and big data can be exploited in improving the decision-making of retailers, and particularly CM decisions. This could help offline retailers gain competitiveness and improve performance. Based on the adoption of an RTLS-based system technology, we have generated useful shopper behaviour insights, which, combined with the sell-out data, can provide a more thorough assessment of the performance of single categories. Furthermore, this new approach has allowed us to develop a new KPI—the CCP—that helps in comparing the sell-out of different categories, normalised with respect to the potential regarding shopper traffic. This index provides information on the actual ability of each category to perform within the store; thus, it represents an effective basis for formulating effective CM decisions. We believe that the category scorecard can be adopted by retailers for discovering new patterns in data (Erevelles et al., 2016) alongside an analytics tool to make more accurate decisions, thereby improving both performance at the overall store level. In particular, the tool could be useful in supporting category managers in their decision-making processes regarding the following issues:

- to define an assortment planning more following the shoppers' needs and behaviours;
- to establish category's goals that are more coherent with consumer-related goals;
- to optimise retail space management, answering questions such as 'how much space to allocate to each category?' and 'where to place each category?';
- to identify new patterns and trends in shopping behaviours.

Answering these issues based on a true knowledge of shopper behaviour allows retailers to focus on their categories' investments to better identify merchandising strategies that could improve store performance (Begley and MacKenzie, 2018). Moreover, our research shows how retailers can exploit the potential of big data. In particular, we believe that shopper behaviour analysis could allow retailers to enrich their knowledge about both customers and store performance. From a managerial viewpoint, the acquisition of new data-driven knowledge resulting from the combination of multiple data sources (Bradlow et al., 2017), such as those of shopper behaviour and transactional ones, can guarantee retailers new sources of competitive advantage (Kumar et al., 2017; Grewal et al., 2017).

10. Limitations and directions for future research

This research presents some limitations related to both the technology/methodology and the validity of the results in other contexts. Although the sample was extremely large (dataset comprised 18,476 shoppers and a total of 85,449 SKU purchases analysed, equal to a turnover of €839,252.68), it referred to data coming from a single store. Thus, the results we obtained were strictly linked to the specific context (store format, location, shopper target, detection period) in which the data were collected, and more general observations of categories' performance could be made very carefully. However, this research contributes to the CM studies regarding how to measure category performance and not to evaluate the categories' performance. Another limitation is strictly linked to RTLS technology, which helps in detecting only the shoppers using a cart or a basket and, therefore, cannot consider all those individuals who make a short shopping trip or purchase few products without using a cart or a basket. For future research, it would be interesting to repeat the study in different locations, types of store formats, and periods to verify the proposed scorecard's effectiveness in evaluating the categories' performance. Another interesting research stream could be to analyse the impact of decisions based on the proposed indicators. For example, for the one we analysed, the effectiveness of a store layout variation or of the merchandising material to convey traffic towards categories with high CCP values could be tested, monitoring how the performance regarding sell-out and CCP varies and verifying how the categories 'move' within the scorecard. Finally, this research proposes a first approach to study category performance, starting from data based on shopper behaviour analysis; future research should broaden the set of indicators than those proposed in this study to enrich the measurement framework.

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Combining Sell-Out Data With Shopper Behaviour Data for Category Performance Measurement: The Role of Category Conversion Power

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Abstract

Retailers need to manage a series of complex decisions relating to numerous products. To reduce this complexity, they have introduced category management practices, which consider groups of similar products (categories) that can be managed separately as single business units (SBUs). Although the concept that the store offer should be organised as a category mix and that this strategy allows for better overall store management is already consolidated, retailers still struggle to adopt an approach to the store performance measurement starting from a category level perspective. Nowadays, the available methods for measuring categories' performance are quite limited. The current trend sees the measurement of category performance mainly based on sell-out data that are ill-equipped to fully address category management issues. Retailers should broaden their field of analysis not only by focusing on the product/sales perspective but also by including other methodologies such as shopper behaviour analysis. In this regard, the use of technology offers the retail sector new perspectives for those analysis. Therefore, we intend to contribute to the ongoing debate on the retail analytics topic by presenting a shopper behaviour analytics system for category management performance monitoring. More in detail, we could derive a new key performance indicator, category conversion power (CCP), aimed at analysing and comparing the single categories organised within the store. The research is based on a unique dataset obtained from a real-time locating system (RTLS), which allowed us to collect behavioural data togheter with sell-out data (from POS scanner). We argue that retailers could exploit this new analytical method to gain more understanding at the category level and therefore make data-driven decisions aimed at improving performance at the store level.

Keywords: Category management, Performance Measurement, Shopper behavior, Retail marketing, RTLS technology, Big Data

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1. Introduction

The retail landscape has greatly changed during the last few years—in terms of consumers' behaviours, new forms of competition and technologies. One of the most enduring trends is the growing breadth and depth of assortments, following the growing sophistication and differentiation of consumer demand. This poses new challenges for retailers who need to manage a series of more complex decisions. To reduce this complexity, they introduced category management practices. Category management (CM) entails considering a group of similar products as a single business unit (category), which can be managed separately from others Nielsen (1992). The importance of CM is well recognised by both practitioners (ECR, 2020) and academics Voleti et al. (2017), Gooner et al. (2011). It has played a germane role in the evolution of retail marketing since its introduction in the late 1980s; however, as the retail landscape has changed a lot, some evolution in CM practices is also needed. Generating insights into consumer shopping behaviour and the shopper journey is becoming increasingly strategic to develop and implement superior category solutions and win competition with a differentiated shopping experience (ECR, 2020). Hence, a relevant issue is the performance measurement of categories. Retailers still struggle to adopt an approach to store performance measurement starting from a category level perspective. Traditionally, they rely on sales data to measure category performance. Indeed, categories sell-out is crucial for retailers not only to a turnover perspective, but also to understand each category marginality. Therefore retailers use sales data to understand which categories contribute to keep high volumes, which is fundamental to stay in the market and which ones contribute more to their mark up, which is crucial to be overall profitable. However, as stated by Desrochers and Nelson (2006), sales data are ill-equipped to fully address CM issues. For example, if an item has been concurrently sorted into more than one category, scanner data cannot identify from which category a sale was made. Moreover, sales data cannot show whether the product performance regarding revenues depends on the shelf position (shelf planogram), the category position inside the store (store layout), the product availability (stock level), etc. Definitely, sell-out data cannot explain category performance if not supported by other information related to in-store shoppers' behaviour. To face these measurement issues, retailers should broaden their field of analysis by focusing on other sources and types of data than product sales, such as shopper behaviour analysis Ferracuti et al. (2019). Combined with scanner data, these could offer vital insights to implement CM more effectively. Shopper behaviour analysis can benefit greatly from the new opportunities offered by technological advances Grewal et al. (2018), Ferracuti et al. (2019), Kaur et al. (2020). Some of the most relevant studies explore technology as a possible 'bridge' between the online and offline dimensions, useful for analysing and understanding in-store purchasing behaviours Schnack et al. (2021) , Aw et al. (2021). Data on customers' browsing ('path data') and purchase ('intent to buy' by adding to cart, abandoning the cart, etc.) behaviours that were once available only to online retailers are now being integrated into physical stores Boone et al. (2019), thanks to new in-store technologies. Traffic counters, infrared sensors, and video cameras can now track customer traffic and paths through the store, generating a lot of in-store data related to customer behaviour. Combining 'new' and 'old' sources of data, nowadays 'retailing is at the centre of a storm of big data opportunities and challenges', which calls for more research on how to derive value from them (Dekimpe, 2020). Retailers are seeking means to exploit the huge amount of collected shopper data (e.g. what they purchase, how they move in the stores, etc.) to extract valuable knowledge that facilitates effective decisions. However, more research is needed to objectively document the advantages of adopting a (big) data-driven approach. Based on these premises, our research fits at the crossroads of two research streams—the effective measurement of categories' performance and the effective use of big data to generate insights into shopping behaviours—and our scope is brick-and-mortar retail environments. Our focus is not to explore and understand the complex shopping behaviour, investigating the motivations and stimulus behind the purchase decision, but to obtain a quantitative representation of the shoppers' behaviour in store. Accordingly, the aims of this study are twofold:

1. To introduce a more effective CM scorecard of indicators.
2. To objectively demonstrate the usefulness of big data for retailers' strategies and how to extract value from them.

In particular, we propose a new key performance indicator—category conversion power (CCP)—which combines sell-out data with shopping behavioural data, answering the recent call of Ferracuti et al. (2019). Starting from that, we argue that retailers could get a more comprehensive understanding of the performance at the category level and therefore make data-driven decisions aimed at improving the performance at the store level. Following the above discussion, the rest of the paper is structured as follows: Sections 2 and 3 review the relevant literature and research design, respectively; Section 4 describes the methods; Section 5 outlines the main results; and Sections 6 and 7 discuss the implications and conclusions, respectively.

2. CM in retail: The category performance measurement issue

In searching for new ways to improve the store's competitiveness and performance, CM is one of the most challenging marketing tasks for retailers Hübner (2011) Hübner and Kuhn (2012). Approaching CM means for manufacturers and retailers to change their focus from individual brands to overall product category performances Desrochers and Nelson (2006). According to Blattberg and Fox (1995), a category is a distinct, manageable group of products that consumers perceive to be related and/or substitutable in meeting a consumer need. Thus, CM means managing categories as strategic business units Dupre and Gruen (2004). As a pillar of efficient consumer response (ECR) practices, CM is aimed at supporting retailers in providing the right mix of products, the right price, with the right promotions, at the right time, and at the right place Gruen and Shah (2000). Several studies have examined and confirmed the positive impact of CM practices on store performance Gooner et al. (2011), Dupre and Gruen (2004), Basuroy et al. (2001) , Dhar et al. (2001), Gruen and Shah (2000), Zenor (1994). Although the topic has been studied from different perspectives, a common vision emerges: the authors agree that there is a need to plan, implement, and measure categories as single entities to optimise their coordination within the store. In considering CM as a strategic process Blattberg and Fox (1995), the category performance measurement is a critical activity. Knowing the category performance may be useful to assortment planning, define promotional programmes involving related categories, understand the best position for merchandise material, and study store layouts' performance, etc. Furthermore, the need for a scorecard of indicators for the CM was already exposed in 1995 by the CM Subcommittee of the ECR Best Practices Operating Committee and the Partnering Group Inc. Until now, the most common methods have been based on sales data. Scanner data are employed for different purposes: to understand interrelation among different stock keeping units (SKUs) to group highly interrelated products into categories, such as milk, cream, and butter in the 'Dairy category' Nielsen (1992), Gooner et al. (2011); to identify cross-category interrelations to provide powerful pieces of information in the process of understanding and managing the retailer's business Tanusondjaja A (2016), Hruschka H (2011), Srinivasan S (2011), Seetharaman P B (2005), Russell G J (2000), etc. Following the same perspective, Musalem et al. Musalem et al. (2018) used shopping basket data (products sold, units sold, date, and time for each purchase recorded in a single month from a mid-sized supermarket in Latin America) to detect interrelations among product categories. However, retailers still struggle to adopt a set of indicators at the category level, which integrates different data other than scanner based one. According to Desrochers and Nelson Desrochers and Nelson (2006), sales data are ill-equipped to fully address CM issues, and they need to be integrated with other information related to in-store shoppers' behaviour to provide a full category performance understanding. The CM process can be improved by adding shopper behaviour insights to traditional point-of-purchase scanner information. In this way, manufacturers and retailers can answer a set of strategic questions, such as 'how much space to allocate to each category?', 'where to place each category?' or 'how does each category perform?'. In this context, technology, particularly big data analytics, can play a great role in enabling new CM decision support systems (ECR, 2020) Hübner (2011).

3. The 'empirical science' of in-store shopper behaviour

Understanding shopper behaviour is one of the keys to success for retailers, and shopper behaviour metrics are imperative in the retail industry due to their direct influence on performance indicators Phua et al. (2015). Answering questions—such as which retail attributes are important to which shoppers and how shoppers behave within different store formats and shelf layouts—provides powerful insights for manufacturers and retailers who want to improve the in-store shopping experience Ferracuti et al. (2019). Research on shopping behaviour has a long tradition, and various issues have been investigated over years. Many studies focused on the relative importance of in-store features, such as retail atmosphere and smell Chebat et al. (2000), Yalch and Spangenberg (2000), Solomon (2010); colour McKenna (2020), Guild and Wilhide (1992); music Morrison et al. (2011), Solomon (2010); merchandise Baker et al. (1994); moods, layout, signage, fixtures, and fittings Newman et al. (1996), etc. Also, the relevance of in-store advertising is being increasingly recognised Schneider and Rau (2009), Harris (2009). From a methodological standpoint, different methodologies have been implemented, ranging from conventional methods (such as surveys) to laboratory or field experiments. It is well recognised that natural observation of shoppers in-store offers some unique advantages compared to laboratory experiments or shoppers' self-reports Sorensen et al. (2017), which are based on customer's retrospective recall. Procedures for tracking in-store shopper behaviour appeared in the marketing literature during the 1960s Granbois (1968) and were conducted mainly by manual observation of the researcher at the point of sale. More recently, technological advances have offered new tracking tools, such as radio frequency identification (RFID) tags attached to baskets/shopping carts, Bluetooth through mobile phones Phua et al. (2015), and video observation. They allow data collection in an unobtrusive, real-time, and inexpensive way Landmark and Sjøbakk (2017). These procedures were foundational to the 'empirical science' of shopper behaviour Larsen et al. (2020), Seiler and Pinna (2017). Therefore, new sources of in-store data related to in-store shopper behaviour have emerged: traffic data—related to the number of shoppers entering the store, and path data—related to the subsequent interactions with various store elements before making a purchase decision. For example, Kanda et al. Kanda et al. (2008) tracked shoppers' trajectories with sensors to predict shoppers' future behaviours. Hui et al. S Hui (2009) used data collected through RFID tags to verify the behavioural hypothesis on customers' purchase processes. Moreover, Sorensen et al. Sorensen et al. (2017) and Landmark and SjØbakk Landmark and Sjøbakk (2017) adopted the RFID system to conduct an analysis on shopping patterns in retail stores. In particular, the first ones demonstrated the possibility to collect a large amount of data from different sources - different countries, different store formats and different store sizes - to identify consistent patterns of shopper behaviour, laying the foundations for future empirically grounded theory of shopper behaviour. Lu et al. Lu et al. (2013) measured the effect of queues on customer purchases using data on a queuing system (collected via video recognition technology) combined with point-of-sales data. Ferracuti et al. Ferracuti et al. (2019) applied a real-time locating system (RTLS) to detect shopping paths and provide preliminary shopping trip segmentation. Their work represents a starting point in studying shopping movement inside the store, paving the way for integration with sell-out data; they introduced an index for measuring the attraction level of each area of the store - in terms of the average number of people visiting and the permanence time - and a novel method for estimating the probability of a path. However they does not consider purchasing behaviour. Although a growing interest in using these technologies in retail is noteworthy, the analyses conducted by the aforementioned studies have produced outputs, mainly at the store level. In this work, we intend to contribute to the existing literature by providing insights at the single category level. Hence, if it is true that CM is necessary for performance improvement at the store level Gooner et al. (2011), Dupre and Gruen (2004), it is equally fundamental to introduce methodologies that examine performance at the category level and allow a comparison among them Musalem et al. (2018).

4. The 'storm' of big data

The new sensors and tracking systems represent new sources of data that contribute to the phenomenon of big data in retailing, thanks to technological advancements. Nowadays, retailers can integrate different data sources Bradlow et al. (2017): CRM and POS systems, credit cards or loyalty cards, email, in-store visits, web logs, social media data, etc. They may use big data for several purposes, including consumer trend analysis, future demand forecasting, understanding consumer needs and motivations, improving cross-selling, enhancing pricing, offering customised product recommendations, implementing market segmentation, etc. Large volumes of unstructured and structured data from various sources contain valuable insights into shopper behaviour, which could contribute to the growth of retail businesses. Considering this transformation, data are changing into something that is much more dynamic and fluid, generated daily through various consumer interactions. The rapid growth in consumer-generated big data—which are mostly sourced from various types of mobile devices and sensor technologies—has created new challenges for retailers in leveraging such data within their decision-making practices. Retailers are still struggling to exploit the huge amount of collected shopper data (e.g. what they purchase, how they move in the stores, etc.) for extracting valuable knowledge that facilitates effective decisions. Consequently, there is a growing need to address questions on how to make sense of these vast amounts of raw information, answering the so-called 'big data gap' Aversa et al. (2021).

5. Research design

5.1. The technology

To collect shopper behaviour data, we decided to use an RTLS based on ultrawide band (UWB) technology applied in a real-world German supermarket. As already demonstrated in Ferracuti et al. (2019), RTLS is a suitable and profitable technology for indoor location purposes M Paolanti (2017), Contigiani M (2016), Sturari M (2016). The three phases that concerned the RTLS tracking and the successive creation of the dataset were as follows:

1. Monitoring the in-store shopper path through tags and anchors; tags were integrated with the shopping carts and baskets for tracking the path and sending data to the anchors; anchors are the antennas installed in the ceiling of the store to form a homogeneous grid that covers it entirely; they collect data from the tags and forward them to the RTLS server;
2. Sending the data collected by the RTLS to a cloud server;
3. Processing and storing data in a database. During this phase, the system filters eventual noise and anomalies based on the following two hypotheses: the first is that the points with an attraction time of less than five seconds are filtered since it is too short for the trajectories crossed in less than two minutes; the second is that for a basket or cart stopped for more than five minutes, we consider a novel trajectory since it is assumed that it is taken by another buyer.

5.2. Experiment: Context and methodological choices

The experiment was conducted in a German supermarket during business hours for three weeks (from 08/28/2017 to 09/16/2017, according to the sell-out data received from the

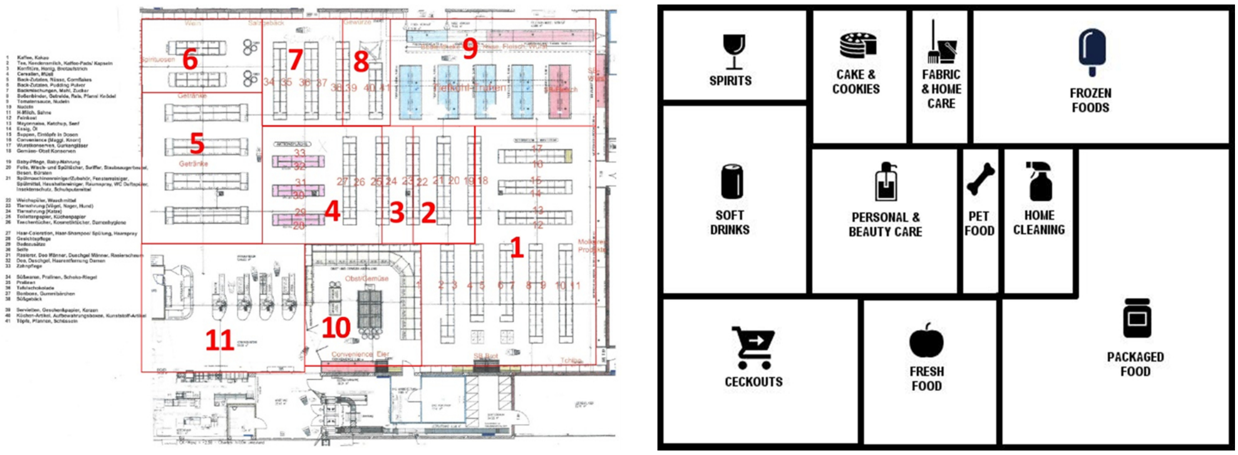

Figure 1: Store layout (left) and categories (right)

store), i.e. 18 days (considering that on Sunday the store is closed). We analysed shoppers' behaviour in 10 categories, which are shown and numbered in Figure 1.

The following categories were defined by grouping departments in which highly interrelated products Nielsen (1992), Gooner et al. (2011) were sold:

- Packaged Food
- Fabric and Home care
- Pet food
- Personal Beauty care
- Soft drinks
- Spirits
- Cakes and cookies
- Home cleaning accessories
- Fresh food
- Frozen food

To analyse the categories, the store layout has been ideally divided into a grid to determine each basket and cart exact position. Each cell of the grid corresponds to a real store area measuring 20 cm × 20 cm. The RTLS allows us to count exactly how many carts and baskets that passed on each cell (area of the store), the relative stay time, and to recreate the exact shopper path inside the store, aggregating cells where the cart/basket passed. Also, it is possible to determine exactly the 'walkable metres' in reference to both the store and each category, defined as the sum of the cells where there is no structural store element (shelves, walls, displays, check-out, etc.), which prevents the shoppers' passage, thanks to this system. Finally, we selected the areas corresponding to categories on the store layout and plan and obtained the 'coordinates' needed to extract for each category the relevant data from the database. Once the category area was defined through the relative coordinates, it was possible to extract the total passing carts/baskets in that area in a specific period, the average stay time, and the distance travelled by the carts/baskets in that area, obtaining a full overview of each category traffic flow. The RTLS tags are linked to carts/baskets and not to a single person; this means that each time a cart/basket enters a specific area, the system counts a new passing, regardless of the person holding the cart/basket. Considering this, for the data extraction phase, it was decided to include the corridors adjacent to the categories in the coordinates of each area. In this way, we avoided counting twice a shopper entering a category from the corridor, then going out from that same corridor, and entering the category again. In Figure 2, we represent the subdivision of the store into the category areas, resulting from the process previously illustrated (picture 'a': in blue store walls, shelves, and displays, in orange store check-out, in green store entrance), the category borders (picture 'b'), and the resulting category areas (picture 'c').

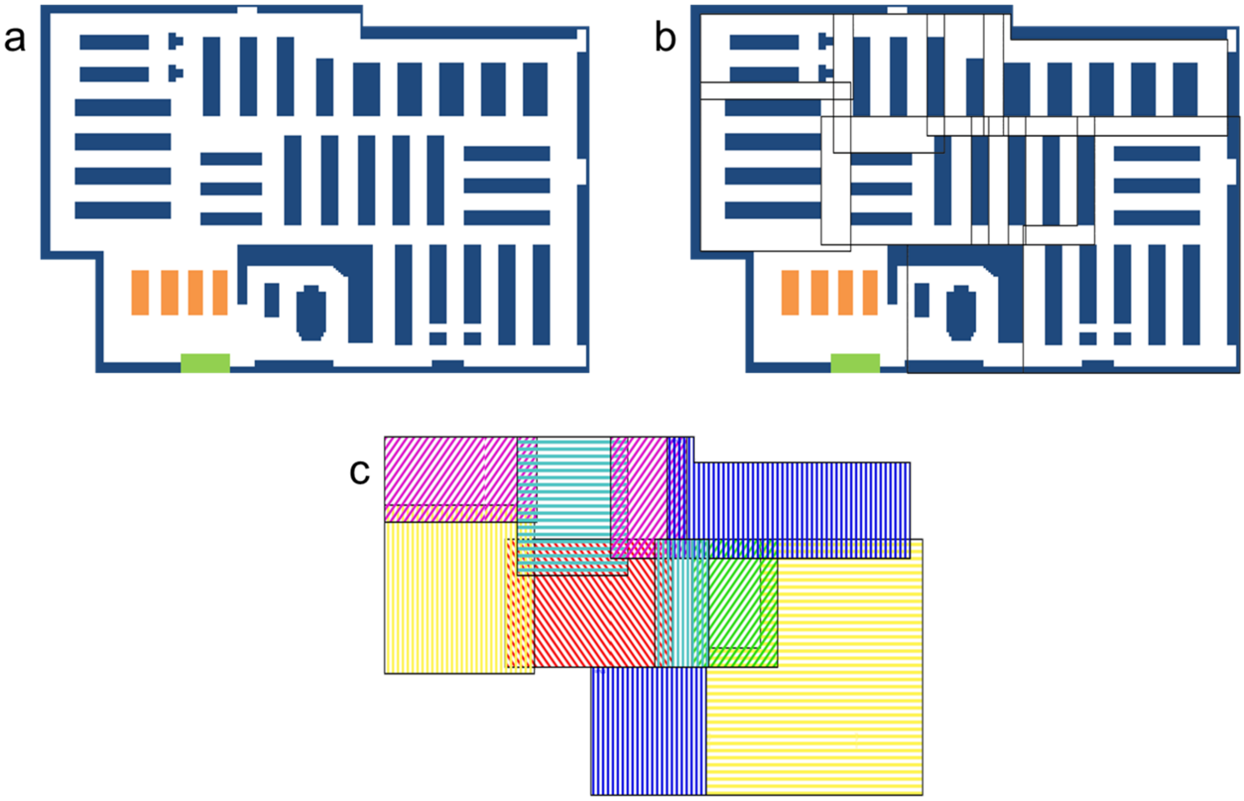

Figure 2: Store subdivision into category areas

6. Main findings

Table 1 shows the sell-out data and behavioural data obtained by the RTLS for each category.

SECTOR	PASSING	AVG DISTANCE	AVG SECTOR DWELL TIME	WALKABLE METERS	TOT Volume (Packs)	TOT Volume (L/kg)	TOT Value (EUR)
PACKAGED FOOD	12.723	36,46	03:04	241,96	51.412,12	20.342,26	86.777,46
FABRIC AND HOME CARE	9.912	6,55	00:20	48,72	3.473,85	2.151,85	8.233,38
PET FOOD	5.697	4,92	00:14	29,28	6.048,63	1.735,74	5.461,87
PERSONAL BEAUTY CARE	12.008	12,74	00:51	121,68	6.292,79	806,66	13.967,95
SOFT DRINKS	12.162	14,60	01:25	142,84	13.059,97	24.888,05	18.917,33
SPIRITS	3.776	11,79	00:35	82,88	5.943,48	4.668,91	18.217,70
CAKES AND COOKIES	8.885	11,86	00:43	84,64	15.935,43	2.801,01	22.619,59
HOME CLEANING ACCESSORIES	6.670	9,15	00:31	52,76	1.486,70	119,71	2.535,42
FROZEN FOOD	12.715	15,37	01:32	132,48	61.796,24	22.412,17	93.846,70
FRESH FOOD	8.585	18,24	01:31	54,32	10.845,90	5.597,53	19.566,15

Table 1: Sell-out and behavioural data for each category

Based on these data, we proposed a variation in the gross rating point (GRP_i) index, already developed by Ferracuti et al. (2019). They defined GRP_i as a measure of the category performance in terms of reach and frequency by multiplying the number of people passing by with the average time spent in each department of the store; this index was then normalised considering the size of each department, inducing the following formula: $GRP_i =$ (People $\times$ AVGti)/m2. To better describe the way in which shoppers navigate the category, we proposed to use the previously defined ‘walkable metres’ in place of ‘total area’ of the category because the former represents the actual category area where shoppers can walk through. In this way, the previous GRP_i is calculated as follows: $GRP_i =$ (Passing $\times$ AVG sector dwell time)/walkable meters.

7. The CCP Index: A New KPI

As already said, the GRP_i provides a measure of performance in terms of reach and frequency: the bigger GRP_i is, the more the category is visited by a greater flow of shoppers and for a longer period. It could therefore be assumed that a category with a high GRP_i is a store area that has high potential regarding the number of shoppers and exposure time. For the German supermarket we analysed, the fresh food category was the category with the highest GRP_i (Table 2).

Table 3 Ranking of categories based on sell-out data.

Comparing the value of GRP_i to the sell-out data for each category, retailers could measure the impact of the current strategy of the category and understand which categories need a change. For example, while the ‘Fresh food’ and ‘Packaged food’ categories ranked the top positions in both rankings, the ‘Fabric home care’, ‘Home cleaning accessories’, and ‘Pet food’ categories were the least performing, ranking the last positions in both index. However, there are some categories that showed a performance hard to understand because they have a good position in a ranking and a poor one in the other. To solve this dilemma, we introduced the ‘CCP’ index, defined as follows: CCPi = (Total value of category)/GRP_i. Using this new index helps in comparing the sell-out data of different categories, which are

Nr	Category	GRP_i
1	Fresh food	14382.09
2	Packaged food	9675.29
3	Frozen food	8829.86
4	Soft drinks	7237.26
5	Personal beauty care	5032.94
6	Cakes & cookies	4513.88
7	Fabric & home care	4068.97
8	Home cleaning accessories	3919.07
9	Pet food	2723.98
10	**Spirits**	**1594.59**

Table 2: GRP_i = Passing × AVGti sector dwell time / walkable meters (m2)

Nr	Category	TOT (Euro)
1	Frozen food	93846.70
2	Packaged food	86777.46
3	Cake & cookies	22619.59
4	Fresh food	19566.15
5	Soft drinks	18917.33
6	**Spirits**	**18217.70**
7	Personal beauty care	13967.95
8	Fabric & home care	8233.38
9	Pet food	5461.87
10	Home cleaning accessories	2535.42

Table 3: sell-out of each category

normalised regarding the potential for shopper traffic (passing and stay time) within each category, expressed by GRP_i. Table 4 presents a novel category ranking based on the CCP index: when the index presents relatively high values, it means that the category is strong in converting traffic flow in sales. However, when the CCP index presents a low value, it means that the category cannot convert the high traffic into purchases.

8. The CCP scorecard

To understand how the CCP index is determined by the different categories' sell-out performances, especially when categories have the same potential traffic flow, we used 'data visualisation', associating the CCP value of each category with the corresponding turnover. In this way, we can obtain a scorecard where each category can be considered a 'strategic business unit', which is useful for formulating category management strategies. In Figure 3, we illustrate our CCP scorecard based on two dimensions: the total value (sell-out, Euro) and the CCP of each category.

Nr	Category	CCP
1	**Spirits**	**11.42**
2	Frozen food	10.63
3	Packaged food	8.97
4	Cake & cookies	5.01
5	Personal beauty care	2.78
6	Soft drinks	2.61
7	Fabric & home care	2.02
8	Pet food	2.01
9	Fresh food	1.36
10	Home cleaning accessories	0.65

Table 4: CCP of each category

The scorecard based on the CCP (Figure 3) aims to identify the actual ability of each category to perform within the store, allowing professionals to make more effective strategic category management decisions. Considering the results illustrated in Figure 3, the 'Frozen Food' and 'Packaged Food' categories are the best-performing categories—those characterised by high sell-out and high CCP values. These are the less problematic categories because they can convert the high potential in terms of traffic in sell-out. Therefore, managers should continue to invest in these categories, capitalising on their high 'power' to convert traffic into sales (high CCP value). The categories 'Fabric home care', 'Home cleaning accessories', and 'Pet food' are the worst—those characterised by low values in both indicators. Considering their low ability to convert traffic into sell-out, managers could decide, for example, to move these categories towards the less strategic and low performance store areas, modifying the store layout. Above all, the scorecard allows professionals to better understand and manage the categories with low sell-out in absolute value but good (or excellent) performance in terms of CCP, such as the 'Spirits' category; considering the not-bad potential to convert traffic, managers could increase the number of shoppers visiting this category and/or the stay time to increase sell-out 'Spirits'. Looking only at the sell-out data and traffic data (GRP_i), managers may be led to think of disinvesting from this category; however, the CCP index is the highest, showing the very high potential of this category to convert the shopper flow into turnover. Hence, it could be considered a strategic category, and it could be very convenient to invest in some store marketing initiatives to increase the traffic flow and/or the time spent in category. 'Spirit' proved to be the category with the greatest conversion power but with a potential in terms of traffic flow still unexpressed compared to the average store potential. In this analysis, the necessity of an increase in the number of shoppers and in the stay time to obtain a given increase in sell-out was unexplored. Future studies are required in this sense. In any case, to determine which of the two strategies induces a greater increase in turnover, a category manager could test different category strategies, aiming to increase the traffic flow in the category (for example, through cross-promotions with other categories or by placing promotional material in the categories with the highest traffic to convey a greater flow in the category) and to increase

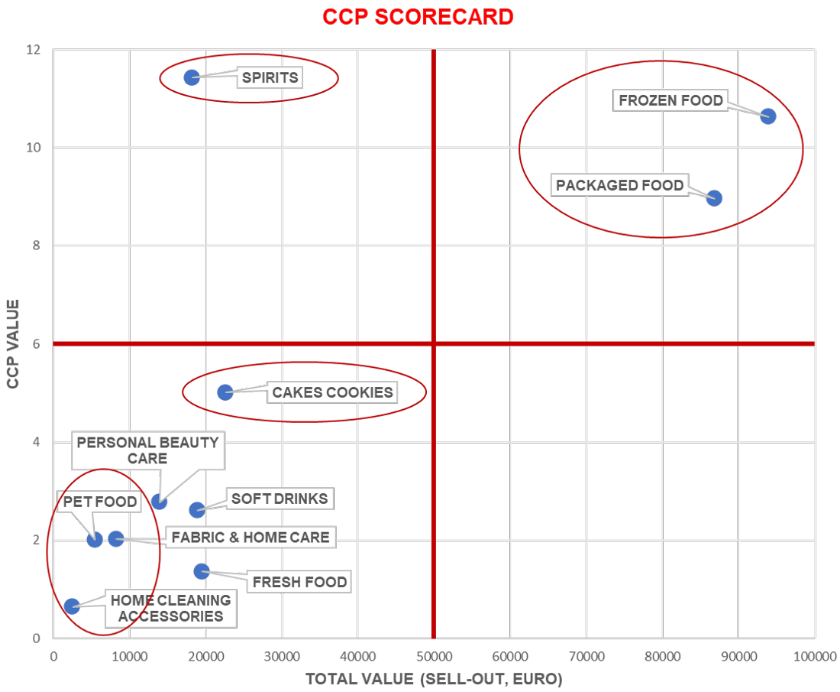

Figure 3: CCP scorecard

the time spent in the category (for example, by placing communication merchandising material in category, such as free-standing display units, shelf edging, digital signage, posters, banners, etc.). It should not be surprising that there are no categories in the fourth matrix quadrant—those with high turnover in the presence of a low CCP—and that it is closely related to the CCP formulation. Indeed, the CCP is calculated by comparing the category sell-out volume with the GRP_i value, an expression of the category traffic volume. Therefore, for a low CCP value, there should be low sales performance compared to other store categories. If the sales and traffic volumes were equally high, we would have an average CCP value, as in low traffic volume and low sales performance. However, if the sales performance was high with low traffic, we would get a maximum CCP value (as for 'spirit' category). Therefore, the condition to obtain a low CCP value is necessarily the concomitant presence of high traffic volumes with poor sales performance or high sales performance but with a traffic volume (which is the denominator) tremendously higher than other categories (which is of course possible from a theoretical viewpoint, but improbable in reality, or related to an extremely specific situation). Obviously, it is necessary to talk about low, high, and medium performances of traffic or sales in a relative way by comparing the categories with each other within the same store over the same period.

9. Discussions

9.1. Theoretical implications

From a theoretical perspective, the paper contributes to the academic debate on the topic of category management and its impact on store performance Gooner et al. (2011); Dupre and Gruen (2004); Dhar et al. (2001); Gruen and Shah (2000). The study lays its foundations on the vision of CM adopted by Dupre and Gruen (2004) who consider each category within the store as a single strategic business unit. This approach is consistent with Desrochers and Nelson's Desrochers and Nelson (2006) recommendations to retailers to change their focus from individual brands to overall product category performances. Starting from these assumptions, the paper proposes a new approach to category management performance measurement based on the combination of sell-out data with shopper behaviour data. Consistently with Desrochers and Nelson's Desrochers and Nelson (2006) argument, the results show that sell-out data analysis alone is not sufficient to provide an adequate measurement of the performance of the single category and it could also be misleading for retailers. In this context, by using shopper behaviour metrics, the paper addresses the need of more comprehensive performance indicators Phua et al. (2015); Sorensen et al. (2017); Ferracuti et al. (2019); Larsen et al. (2020).Accordingly, the paper has identified a new key performance indicator, Category Conversion Power (CCP), which combines sell-out and shopper behaviour data sources. From a methodological point of view, the paper adopts RTLS technology M Paolanti (2017); Contigiani M (2016); Ferracuti et al. (2019); Sturari M (2016). The innovative techniques proposed, offer scholars and retailers' new measurement opportunities which, as stated by Boone et al. (2019), allow a greater convergence between the online and offline retail dimensions. Accordingly, the paper intends to contribute to shopper behaviour analysis in the physical retail sector.

9.2. Practical Implications

This paper provides several implications for retail managers, especially for those operating in the physical store sector. In fact, while the e-commerce purchasing process takes place entirely in the online environment and can therefore be easily monitored and measured, offline retail processes do not provide the same amount of data. In this sense, the work contributes to the consolidation of a data-driven approach that can be implemented thanks to the adoption of technologies capable of generating new data sources at support to retailers. Big data analytics can, overall, produce more exhaustive strategic insights than analysis based on single sell-out data or on direct observations of in- store shopper behaviours. Nonetheless, the proposed approach should not be considered as a replacement to the traditional analysis techniques at the point of sale but, instead, as either integrative or alternative. Existing approaches, as they are based on research methodologies such as direct observations, surveys, focus groups, laboratory-shops or "re- constructed" supermarkets, must recruit potential buyers in order to monitor their behaviours. By contrast, the proposed approach allows retailers to adopt a larger-scale vision that examines purchase paths and times of a much larger shoppers' sample. For example, in one day, the analysed technologies allow to collect data on the entire shopping path of hundreds of people. For

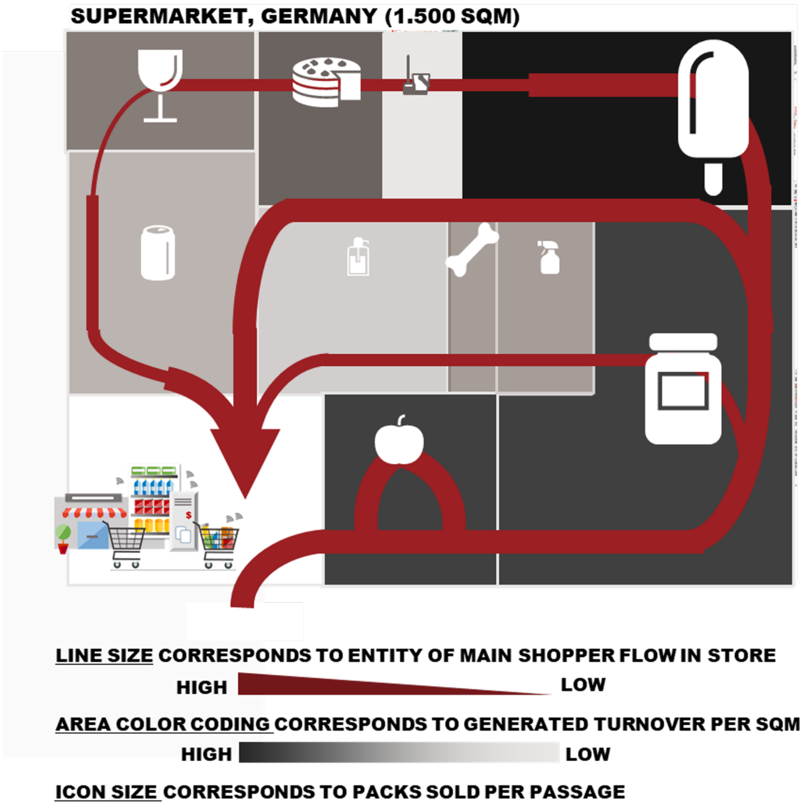

Figure 4: Representation of the store based on some parameters such as the amount of shopper flow in the store, the level of turnover generated per SQM and thenumber of packs sold per passage.

stores of about 800-1000 sqm it is possible to register from 300 to 500 people per day, while, for hypermarkets of about 12,000 sqm, over 7,000 people. Furthermore, on the contrary of other approaches, as buyers are monitored unobtrusively, their behaviours are more likely to preserve authenticity. Nonetheless shoppers' privacy is always protected by the system retaining their anonymity. At the same time, equipping physical stores with technologies such as those used in this work, offers retail managers the possibility to connect the physical store with the digital environment, thus opening up new opportunities for omnichannel strategies. As stated above, the study focuses on CM by proposing a new CCP metric resulting from the combination of sell-out data with shopper behaviour data. Such integration allows retail managers to evaluate the performance of each single category in terms of conversion to purchase. The scorecard, presented as the main output, provides a clearer overview of the contribution of each category to the store. Figures 4 and 5 showcase an application example of the work's findings.

The integration of the generated data with the traffic flow data of each category, has allowed the creation of a diagram that clearly illustrates both the performance of each individual categories and the ways in which shoppers navigate them. As seen in figure 4, it was possible to create a store representation based on parameters such as the amount

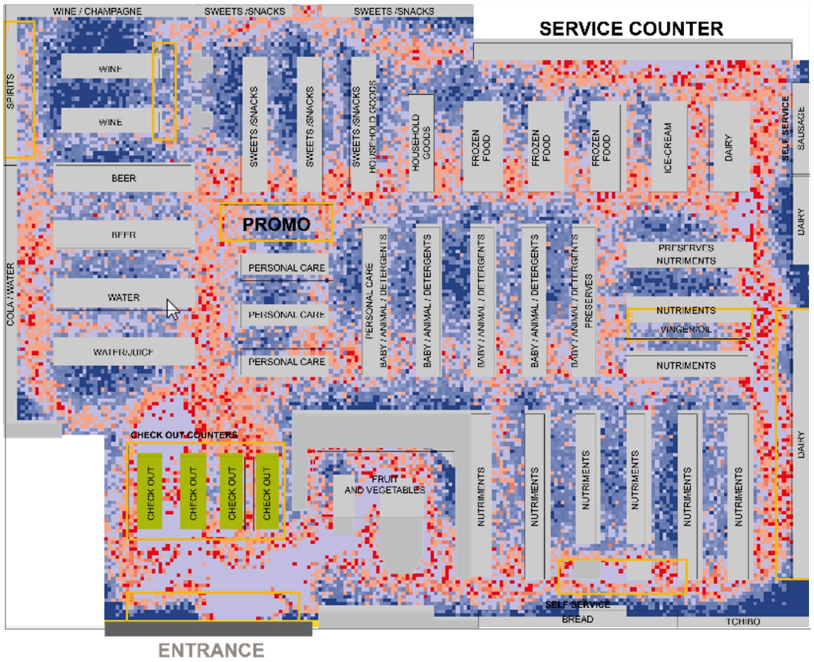

Figure 5: Store heatmap.

of shopper flow in the store, the level of turnover generated per SQM and the number of packs sold per passage. The "category performance map" can also be compared with the store heatmap (figure 5). The "hot" areas are represented in red and they correspond to the highest traffic areas. The "cold" blue areas are characterized by less traffic. Finally, it can be argued that the presented visualization approach, can support retail managers with a deeper awareness of what actually happens inside the store which can therefore be better interpreted with new information. Finally, through this approach, the effectiveness of the choices related to aspects such as store layout, merchandising, promotions, can be tested.

10. Conclusions

Retailing is one of the largest industries in the world and plays a central role in all countries' economy. In Europe, even when limiting oneself to grocery retailing, sales forecasts reach 2289 billion euros by 2022 (IGD, 2018), with millions of people employed in the sector. Given its size and ubiquity, research aimed to contribute to solving the challenges that retail is facing can benefit many stakeholders (Dekimpe, 2020) and counteract the 'Retail apocalypse', that is, the mass closures of many bricks-and-mortar retail stores, particularly in the United States (Peterson, 2017), partially due to the rise in online sales. Our work goes in this direction, showing how the opportunities of technology and big data can be exploited in improving the decision-making of retailers, and particularly CM decisions. This could help offline retailers gain competitiveness and improve performance. Based on the adoption of an RTLS-based system technology, we have generated useful shopper behaviour insights, which, combined with the sell-out data, can provide a more thorough assessment of the performance of single categories. Furthermore, the proposed approach led to the development of a new KPI – the CCP – that compares sell-outs across different categories, normalized according to the potential shoppers' traffic flow. This index provides information on the actual ability of each category to perform within the store; thus, it represents an effective basis for formulating effective CM decisions. We believe that the category scorecard can be adopted by retailers for discovering new patterns in data (Erevelles et al., 2016) alongside an analytics tool to make more accurate decisions, thereby improving both performance at the overall store level. In particular, the tool could be useful in supporting category managers in their decision-making processes regarding the following issues:

- to define an assortment planning following shoppers' needs and behaviours;
- to establish category's goals that are more coherent with consumer-related goals;
- to optimise retail space management, answering questions such as 'how much space to allocate to each category?' and 'where to place each category?';
- to identify new patterns and trends in shopping behaviours.

Answering these issues based on a true knowledge of shopper behaviour allows retailers to focus on their categories' investments to better identify merchandising strategies that could improve store performance (Begley and MacKenzie, 2018). Moreover, our research shows how retailers can exploit the potential of big data. In particular, we believe that shopper behaviour analysis could allow retailers to enrich their knowledge about both customers and store performance. From a managerial viewpoint, the acquisition of new data-driven knowledge resulting from the combination of multiple data sources (Bradlow et al., 2017), such as those of shopper behaviour and transactional ones, can guarantee retailers new sources of competitive advantage (Kumar et al., 2017; Grewal et al., 2017).

11. Limitations and directions for future research

This research presents some limitations related to both the technology/methodology and the validity of the results in other contexts. Although the sample was extremely large (dataset comprised 18,476 shoppers and a total of 85,449 SKU purchases analysed, equal to a turnover of €839,252.68), it referred to data coming from a single store. Thus, the results we obtained were strictly linked to the specific context (store format, location, shopper target, detection period) in which the data were collected, and more general observations of categories' performance could be made very carefully. However, this research contributes to the CM studies regarding how to measure category performance and not to evaluate the categories' performance. Another limitation is strictly linked to RTLS technology, which helps in detecting only the shoppers using a cart or a basket and, therefore, cannot consider all those individuals who make a short shopping trip or purchase few products without using a cart or a basket. The study also presents some limitations in relation to shoppers behaviour. As a matter of fact, the adopted technology allowed to understand how a shopper behaves within the store in terms of time spent, shopping journey and purchases. However, there are other factors that could also be taken into consideration. For example, previous studies recognized product price, perceived quality, brand awareness, time, seasonality, consumption frequency, after-sale services or guarantee, etc. as factors capable of influencing shoppers behaviour. The aim of this study is not to discover best practises in terms of category management or to understand each categories determinants to give general recommendations to professionals and researchers, but it is focused on uncover the potential of Big Data approach, combined with sales data to better measure category performances. For this reason, the store layout and planograms were the one given and were "fixed": it has not been made any changes during the study. In future researches we suggest to investigate more in detail the impact of planogram and layout changes on category performances, as suggested in the discussion section. Finally, a further limitation is the consideration of the shoppers sample as a single segment. In fact, times, shopping routes and money spent may vary depending on shoppers' age. In this regard, new possibilities for segmentation based on variables such as age, sex, but also sentiment, are in the process of being adopted thanks to the introduction of machine learning algorithms in the technologies adopted in the study. For future research, it would be interesting to repeat the study in different locations, types of store formats, and periods to verify the proposed scorecard's effectiveness in evaluating the categories' performance. Another interesting research stream could be to analyse the impact of decisions based on the proposed indicators. Our future work will focus on approaching retailing studies with a more holistic vision. In this sense, first, we are going to create and consolidate the connection between KPI and other factors determining purchase decisions. Second, as the adopted technologies are constantly evolving, there is a need to further validate them as scientific methods. This will result in the introduction of new variables which might improve the current understanding of purchasing behaviours. For example, for the one we analysed, the effectiveness of a store layout variation or of the merchandising material to convey traffic towards categories with high CCP values could be tested, monitoring how the performance regarding sell-out and CCP varies and verifying how the categories 'move' within the scorecard. Finally, this research proposes a first approach to study category performance, starting from data based on shopper behaviour analysis; future research should broaden the set of indicators than those proposed in this study to enrich the measurement framework.

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Combining Sell-Out Data With Shopper Behaviour Data for Category Performance Measurement: The Role of Category Conversion Power

Abstract

Retailers need to manage a series of complex decisions relating to numerous products. To reduce this complexity, they have introduced category management practices, which consider groups of similar products (categories) that can be managed separately as single business units (SBUs). Although the concept that the store offer should be organised as a category mix and that this strategy allows for better overall store management is already consolidated, retailers still struggle to adopt an approach to the store performance measurement starting from a category level perspective. Nowadays, the available methods for measuring categories' performance are quite limited. The current trend sees the measurement of category performance mainly based on sell-out data that are ill-equipped to fully address category management issues. Retailers should broaden their field of analysis not only by focusing on the product/sales perspective but also by including other methodologies such as shopper behaviour analysis. In this regard, the use of technology offers the retail sector new perspectives for those analysis. Therefore, we intend to contribute to the ongoing debate on the retail analytics topic by presenting a shopper behaviour analytics system for category management performance monitoring. More in detail, we could derive a new key performance indicator, category conversion power (CCP), aimed at analysing and comparing the single categories organised within the store. The research is based on a unique dataset obtained from a real-time locating system (RTLS), which allowed us to collect behavioural data togheter with sell-out data (from POS scanner). We argue that retailers could exploit this new analytical method to gain more understanding at the category level and therefore make data-driven decisions aimed at improving performance at the store level.

Keywords: Category management, Performance Measurement, Shopper behavior, Retail marketing, RTLS technology, Big Data

1. Introduction

The retail landscape has greatly changed during the last few years—in terms of consumers' behaviours, new forms of competition and technologies. One of the most enduring trends is the growing breadth and depth of assortments, following the growing sophistication and differentiation of consumer demand. This poses new challenges for retailers who need to manage a series of more complex decisions. To reduce this complexity, they introduced category management practices. Category management (CM) entails considering a group of similar products as a single business unit (category), which can be managed separately from others Nielsen (1992). The importance of CM is well recognised by both practitioners (ECR, 2020) and academics Voleti et al. (2017), Gooner et al. (2011). It has played a germane role in the evolution of retail marketing since its introduction in the late 1980s; however, as the retail landscape has changed a lot, some evolution in CM practices is also needed. Generating insights into consumer shopping behaviour and the shopper journey is becoming increasingly strategic to develop and implement superior category solutions and win competition with a differentiated shopping experience (ECR, 2020). Hence, a relevant issue is the performance measurement of categories. Retailers still struggle to adopt an approach to store performance measurement starting from a category level perspective. Traditionally, they rely on sales data to measure category performance. Indeed, categories sell-out is crucial for retailers not only to a turnover perspective, but also to understand each category marginality. Therefore retailers use sales data to understand which categories contribute to keep high volumes, which is fundamental to stay in the market and which ones contribute more to their mark up, which is crucial to be overall profitable. However, as stated by Desrochers and Nelson (2006), sales data are ill-equipped to fully address CM issues. For example, if an item has been concurrently sorted into more than one category, scanner data cannot identify from which category a sale was made. Moreover, sales data cannot show whether the product performance regarding revenues depends on the shelf position (shelf planogram), the category position inside the store (store layout), the product availability (stock level), etc. Definitely, sell-out data cannot explain category performance if not supported by other information related to in-store shoppers' behaviour. To face these measurement issues, retailers should broaden their field of analysis by focusing on other sources and types of data than product sales, such as shopper behaviour analysis Ferracuti et al. (2019). Combined with scanner data, these could offer vital insights to implement CM more effectively. Shopper behaviour analysis can benefit greatly from the new opportunities offered by technological advances Grewal et al. (2018), Ferracuti et al. (2019), Kaur et al. (2020). Some of the most relevant studies explore technology as a possible 'bridge' between the online and offline dimensions, useful for analysing and understanding in-store purchasing behaviours Schnack et al. (2021) , Aw et al. (2021). Data on customers' browsing ('path data') and purchase ('intent to buy' by adding to cart, abandoning the cart, etc.) behaviours that were once available only to online retailers are now being integrated into physical stores Boone et al. (2019), thanks to new in-store technologies. Traffic counters, infrared sensors, and video cameras can now track customer traffic and paths through the store, generating a lot of in-store data related to customer behaviour. Combining 'new' and 'old' sources of data, nowadays 'retailing is at the centre of a storm of big data opportunities and challenges', which calls for more research on how to derive value from them (Dekimpe, 2020). Retailers are seeking means to exploit the huge amount of collected shopper data (e.g. what they purchase, how they move in the stores, etc.) to extract valuable knowledge that facilitates effective decisions. However, more research is needed to objectively document the advantages of adopting a (big) data-driven approach. Based on these premises, our research fits at the crossroads of two research streams—the effective measurement of categories' performance and the effective use of big data to generate insights into shopping behaviours—and our scope is brick-and-mortar retail environments. Our focus is not to explore and understand the complex shopping behaviour, investigating the motivations and stimulus behind the purchase decision, but to obtain a quantitative representation of the shoppers' behaviour in store. Accordingly, the aims of this study are twofold:

1. To introduce a more effective CM scorecard of indicators.
2. To objectively demonstrate the usefulness of big data for retailers' strategies and how to extract value from them.

In particular, we propose a new key performance indicator—category conversion power (CCP)—which combines sell-out data with shopping behavioural data, answering the recent call of Ferracuti et al. (2019). Starting from that, we argue that retailers could get a more comprehensive understanding of the performance at the category level and therefore make data-driven decisions aimed at improving the performance at the store level. Following the above discussion, the rest of the paper is structured as follows: Sections 2 and 3 review the relevant literature and research design, respectively; Section 4 describes the methods; Section 5 outlines the main results; and Sections 6 and 7 discuss the implications and conclusions, respectively.

2. CM in retail: The category performance measurement issue

In searching for new ways to improve the store's competitiveness and performance, CM is one of the most challenging marketing tasks for retailers Hübner (2011) Hübner and Kuhn (2012). Approaching CM means for manufacturers and retailers to change their focus from individual brands to overall product category performances Desrochers and Nelson (2006). According to Blattberg and Fox (1995), a category is a distinct, manageable group of products that consumers perceive to be related and/or substitutable in meeting a consumer need. Thus, CM means managing categories as strategic business units Dupre and Gruen (2004). As a pillar of efficient consumer response (ECR) practices, CM is aimed at supporting retailers in providing the right mix of products, the right price, with the right promotions, at the right time, and at the right place Gruen and Shah (2000). Several studies have examined and confirmed the positive impact of CM practices on store performance Gooner et al. (2011), Dupre and Gruen (2004), Basuroy et al. (2001) , Dhar et al. (2001), Gruen and Shah (2000), Zenor (1994). Although the topic has been studied from different perspectives, a common vision emerges: the authors agree that there is a need to plan, implement, and measure categories as single entities to optimise their coordination within the store. In considering CM as a strategic process Blattberg and Fox (1995), the category performance measurement is a critical activity. Knowing the category performance may be useful to assortment planning, define promotional programmes involving related categories, understand the best position for merchandise material, and study store layouts' performance, etc. Furthermore, the need for a scorecard of indicators for the CM was already exposed in 1995 by the CM Subcommittee of the ECR Best Practices Operating Committee and the Partnering Group Inc. Until now, the most common methods have been based on sales data. Scanner data are employed for different purposes: to understand interrelation among different stock keeping units (SKUs) to group highly interrelated products into categories, such as milk, cream, and butter in the 'Dairy category' Nielsen (1992), Gooner et al. (2011); to identify cross-category interrelations to provide powerful pieces of information in the process of understanding and managing the retailer's business Tanusondjaja A (2016), Hruschka H (2011), Srinivasan S (2011), Seetharaman P B (2005), Russell G J (2000), etc. Following the same perspective, Musalem et al. Musalem et al. (2018) used shopping basket data (products sold, units sold, date, and time for each purchase recorded in a single month from a mid-sized supermarket in Latin America) to detect interrelations among product categories. However, retailers still struggle to adopt a set of indicators at the category level, which integrates different data other than scanner based one. According to Desrochers and Nelson Desrochers and Nelson (2006), sales data are ill-equipped to fully address CM issues, and they need to be integrated with other information related to in-store shoppers' behaviour to provide a full category performance understanding. The CM process can be improved by adding shopper behaviour insights to traditional point-of-purchase scanner information. In this way, manufacturers and retailers can answer a set of strategic questions, such as 'how much space to allocate to each category?', 'where to place each category?' or 'how does each category perform?'. In this context, technology, particularly big data analytics, can play a great role in enabling new CM decision support systems (ECR, 2020) Hübner (2011).

3. The 'empirical science' of in-store shopper behaviour

Understanding shopper behaviour is one of the keys to success for retailers, and shopper behaviour metrics are imperative in the retail industry due to their direct influence on performance indicators Phua et al. (2015). Answering questions—such as which retail attributes are important to which shoppers and how shoppers behave within different store formats and shelf layouts—provides powerful insights for manufacturers and retailers who want to improve the in-store shopping experience Ferracuti et al. (2019). Research on shopping behaviour has a long tradition, and various issues have been investigated over years. Many studies focused on the relative importance of in-store features, such as retail atmosphere and smell Chebat et al. (2000), Yalch and Spangenberg (2000), Solomon (2010); colour McKenna (2020), Guild and Wilhide (1992); music Morrison et al. (2011), Solomon (2010); merchandise Baker et al. (1994); moods, layout, signage, fixtures, and fittings Newman et al. (1996), etc. Also, the relevance of in-store advertising is being increasingly recognised Schneider and Rau (2009), Harris (2009). From a methodological standpoint, different methodologies have been implemented, ranging from conventional methods (such as surveys) to laboratory or field experiments. It is well recognised that natural observation of shoppers in-store offers some unique advantages compared to laboratory experiments or shoppers' self-reports Sorensen et al. (2017), which are based on customer's retrospective recall. Procedures for tracking in-store shopper behaviour appeared in the marketing literature during the 1960s Granbois (1968) and were conducted mainly by manual observation of the researcher at the point of sale. More recently, technological advances have offered new tracking tools, such as radio frequency identification (RFID) tags attached to baskets/shopping carts, Bluetooth through mobile phones Phua et al. (2015), and video observation. They allow data collection in an unobtrusive, real-time, and inexpensive way Landmark and Sjøbakk (2017). These procedures were foundational to the 'empirical science' of shopper behaviour Larsen et al. (2020), Seiler and Pinna (2017). Therefore, new sources of in-store data related to in-store shopper behaviour have emerged: traffic data—related to the number of shoppers entering the store, and path data—related to the subsequent interactions with various store elements before making a purchase decision. For example, Kanda et al. Kanda et al. (2008) tracked shoppers' trajectories with sensors to predict shoppers' future behaviours. Hui et al. S Hui (2009) used data collected through RFID tags to verify the behavioural hypothesis on customers' purchase processes. Moreover, Sorensen et al. Sorensen et al. (2017) and Landmark and SjØbakk Landmark and Sjøbakk (2017) adopted the RFID system to conduct an analysis on shopping patterns in retail stores. In particular, the first ones demonstrated the possibility to collect a large amount of data from different sources - different countries, different store formats and different store sizes - to identify consistent patterns of shopper behaviour, laying the foundations for future empirically grounded theory of shopper behaviour. Lu et al. Lu et al. (2013) measured the effect of queues on customer purchases using data on a queuing system (collected via video recognition technology) combined with point-of-sales data. Ferracuti et al. Ferracuti et al. (2019) applied a real-time locating system (RTLS) to detect shopping paths and provide preliminary shopping trip segmentation. Their work represents a starting point in studying shopping movement inside the store, paving the way for integration with sell-out data; they introduced an index for measuring the attraction level of each area of the store - in terms of the average number of people visiting and the permanence time - and a novel method for estimating the probability of a path. However they does not consider purchasing behaviour. Although a growing interest in using these technologies in retail is noteworthy, the analyses conducted by the aforementioned studies have produced outputs, mainly at the store level. In this work, we intend to contribute to the existing literature by providing insights at the single category level. Hence, if it is true that CM is necessary for performance improvement at the store level Gooner et al. (2011), Dupre and Gruen (2004), it is equally fundamental to introduce methodologies that examine performance at the category level and allow a comparison among them Musalem et al. (2018).

4. The 'storm' of big data

The new sensors and tracking systems represent new sources of data that contribute to the phenomenon of big data in retailing, thanks to technological advancements. Nowadays, retailers can integrate different data sources Bradlow et al. (2017): CRM and POS systems, credit cards or loyalty cards, email, in-store visits, web logs, social media data, etc. They may use big data for several purposes, including consumer trend analysis, future demand forecasting, understanding consumer needs and motivations, improving cross-selling, enhancing pricing, offering customised product recommendations, implementing market segmentation, etc. Large volumes of unstructured and structured data from various sources contain valuable insights into shopper behaviour, which could contribute to the growth of retail businesses. Considering this transformation, data are changing into something that is much more dynamic and fluid, generated daily through various consumer interactions. The rapid growth in consumer-generated big data—which are mostly sourced from various types of mobile devices and sensor technologies—has created new challenges for retailers in leveraging such data within their decision-making practices. Retailers are still struggling to exploit the huge amount of collected shopper data (e.g. what they purchase, how they move in the stores, etc.) for extracting valuable knowledge that facilitates effective decisions. Consequently, there is a growing need to address questions on how to make sense of these vast amounts of raw information, answering the so-called 'big data gap' Aversa et al. (2021).

5. Research design

5.1. The technology

To collect shopper behaviour data, we decided to use an RTLS based on ultrawide band (UWB) technology applied in a real-world German supermarket. As already demonstrated in Ferracuti et al. (2019), RTLS is a suitable and profitable technology for indoor location purposes M Paolanti (2017), Contigiani M (2016), Sturari M (2016). The three phases that concerned the RTLS tracking and the successive creation of the dataset were as follows:

1. Monitoring the in-store shopper path through tags and anchors; tags were integrated with the shopping carts and baskets for tracking the path and sending data to the anchors; anchors are the antennas installed in the ceiling of the store to form a homogeneous grid that covers it entirely; they collect data from the tags and forward them to the RTLS server;
2. Sending the data collected by the RTLS to a cloud server;
3. Processing and storing data in a database. During this phase, the system filters eventual noise and anomalies based on the following two hypotheses: the first is that the points with an attraction time of less than five seconds are filtered since it is too short for the trajectories crossed in less than two minutes; the second is that for a basket or cart stopped for more than five minutes, we consider a novel trajectory since it is assumed that it is taken by another buyer.

5.2. Experiment: Context and methodological choices

The experiment was conducted in a German supermarket during business hours for three weeks (from 08/28/2017 to 09/16/2017, according to the sell-out data received from the store), i.e. 18 days (considering that on Sunday the store is closed). We analysed shoppers' behaviour in 10 categories, which are shown and numbered in Figure 1.

The following categories were defined by grouping departments in which highly interrelated products Nielsen (1992), Gooner et al. (2011) were sold:

- Packaged Food
- Fabric and Home care
- Pet food

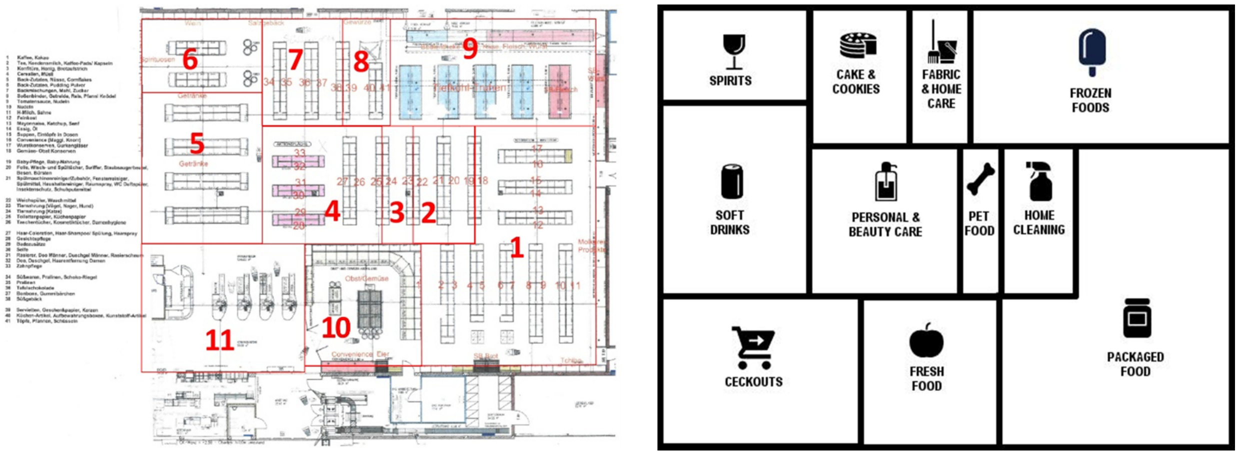

Figure 1: Store layout (left) and categories (right)

- Personal Beauty care
- Soft drinks
- Spirits
- Cakes and cookies
- Home cleaning accessories
- Fresh food
- Frozen food

To analyse the categories, the store layout has been ideally divided into a grid to determine each basket and cart exact position. Each cell of the grid corresponds to a real store area measuring 20 cm × 20 cm. The RTLS allows us to count exactly how many carts and baskets that passed on each cell (area of the store), the relative stay time, and to recreate the exact shopper path inside the store, aggregating cells where the cart/basket passed. Also, it is possible to determine exactly the 'walkable metres' in reference to both the store and each category, defined as the sum of the cells where there is no structural store element (shelves, walls, displays, check-out, etc.), which prevents the shoppers' passage, thanks to this system. Finally, we selected the areas corresponding to categories on the store layout and plan and obtained the 'coordinates' needed to extract for each category the relevant data from the database. Once the category area was defined through the relative coordinates, it was possible to extract the total passing carts/baskets in that area in a specific period, the average stay time, and the distance travelled by the carts/baskets in that area, obtaining a full overview of each category traffic flow. The RTLS tags are linked to carts/baskets and not to a single person; this means that each time a cart/basket enters a specific area, the system counts a new passing, regardless of the person holding the cart/basket. Considering this, for the data extraction phase, it was decided to include the corridors adjacent to the categories in the coordinates of each area. In this way, we avoided counting twice a shopper entering a category from the corridor, then going out from that same corridor, and entering the category again. In Figure 2, we represent the subdivision of the store into the category areas, resulting from the process previously illustrated (picture 'a': in blue store walls, shelves, and displays, in orange store check-out, in green store entrance), the category borders (picture 'b'), and the resulting category areas (picture 'c').

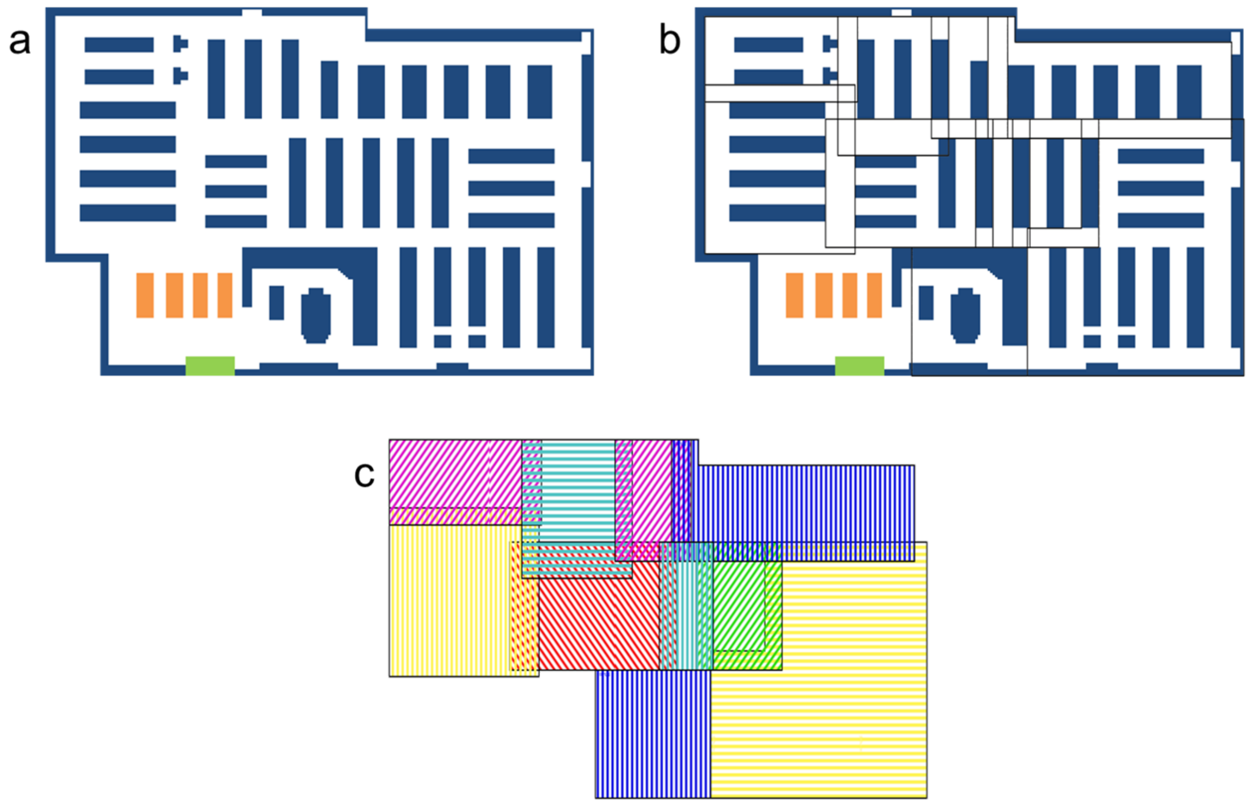

Figure 2: Store subdivision into category areas

6. Main findings

Table 1 shows the sell-out data and behavioural data obtained by the RTLS for each category.

Based on these data, we proposed a variation in the gross rating point (GRP_i) index, already developed by Ferracuti et al. (2019). They defined GRP_i as a measure of the category performance in terms of reach and frequency by multiplying the number of people passing by with the average time spent in each department of the store; this index was then normalised considering the size of each department, inducing the following formula: $GRP_i =$ (People $\times$ AVGti)/m2. To better describe the way in which shoppers navigate the category, we proposed to use the previously defined 'walkable metres' in place of 'total area' of the category because the former represents the actual category area where shoppers can walk

SECTOR	PASSING	AVG DISTANCE	AVG SECTOR DWELL TIME	WALKABLE METERS	TOT Volume (Packs)	TOT Volume (L/kg)	TOT Value (EUR)
PACKAGED FOOD	12.723	36,46	03:04	241,96	51.412,12	20.342,26	86.777,46
FABRIC AND HOME CARE	9.912	6,55	00:20	48,72	3.473,85	2.151,85	8.233,38
PET FOOD	5.697	4,92	00:14	29,28	6.048,63	1.735,74	5.461,87
PERSONAL BEAUTY CARE	12.008	12,74	00:51	121,68	6.292,79	806,66	13.967,95
SOFT DRINKS	12.162	14,60	01:25	142,84	13.059,97	24.888,05	18.917,33
SPIRITS	3.776	11,79	00:35	82,88	5.943,48	4.668,91	18.217,70
CAKES AND COOKIES	8.885	11,86	00:43	84,64	15.935,43	2.801,01	22.619,59
HOME CLEANING ACCESSORIES	6.670	9,15	00:31	52,76	1.486,70	119,71	2.535,42
FROZEN FOOD	12.715	15,37	01:32	132,48	61.796,24	22.412,17	93.846,70
FRESH FOOD	8.585	18,24	01:31	54,32	10.845,90	5.597,53	19.566,15

Table 1: Sell-out and behavioural data for each category

through. In this way, the previous GRP_i is calculated as follows: GRP_i = (Passing $\times$ AVG sector dwell time)/walkable meters.

7. The CCP Index: A New KPI

As already said, the GRP_i provides a measure of performance in terms of reach and frequency: the bigger GRP_i is, the more the category is visited by a greater flow of shoppers and for a longer period. It could therefore be assumed that a category with a high GRP_i is a store area that has high potential regarding the number of shoppers and exposure time. For the German supermarket we analysed, the fresh food category was the category with the highest GRP_i (Table 2).

Nr	Category	GRP_i
1	Fresh food	14382.09
2	Packaged food	9675.29
3	Frozen food	8829.86
4	Soft drinks	7237.26
5	Personal beauty care	5032.94
6	Cakes & cookies	4513.88
7	Fabric & home care	4068.97
8	Home cleaning accessories	3919.07
9	Pet food	2723.98
10	**Spirits**	**1594.59**

Table 2: GRP_i = Passing $\times$ AVGti sector dwell time / walkable meters (m2)

Table 3 Ranking of categories based on sell-out data.

Comparing the value of GRP_i to the sell-out data for each category, retailers could measure the impact of the current strategy of the category and understand which categories need a change. For example, while the 'Fresh food' and 'Packaged food' categories ranked the top positions in both rankings, the 'Fabric home care', 'Home cleaning accessories', and 'Pet food' categories were the least performing, ranking the last positions in both index. However, there are some categories that showed a performance hard to understand because

Nr	Category	TOT (Euro)
1	Frozen food	93846.70
2	Packaged food	86777.46
3	Cake & cookies	22619.59
4	Fresh food	19566.15
5	Soft drinks	18917.33
6	**Spirits**	**18217.70**
7	Personal beauty care	13967.95
8	Fabric & home care	8233.38
9	Pet food	5461.87
10	Home cleaning accessories	2535.42

Table 3: sell-out of each category

they have a good position in a ranking and a poor one in the other. To solve this dilemma, we introduced the 'CCP' index, defined as follows: CCPi = (Total value of category)/GRP_i. Using this new index helps in comparing the sell-out data of different categories, which are normalised regarding the potential for shopper traffic (passing and stay time) within each category, expressed by GRP_i. Table 4 presents a novel category ranking based on the CCP index: when the index presents relatively high values, it means that the category is strong in converting traffic flow in sales. However, when the CCP index presents a low value, it means that the category cannot convert the high traffic into purchases.

Nr	Category	CCP
1	**Spirits**	**11.42**
2	Frozen food	10.63
3	Packaged food	8.97
4	Cake & cookies	5.01
5	Personal beauty care	2.78
6	Soft drinks	2.61
7	Fabric & home care	2.02
8	Pet food	2.01
9	Fresh food	1.36
10	Home cleaning accessories	0.65

Table 4: CCP of each category

8. The CCP scorecard

To understand how the CCP index is determined by the different categories' sell-out performances, especially when categories have the same potential traffic flow, we used 'data visualisation', associating the CCP value of each category with the corresponding turnover. In this way, we can obtain a scorecard where each category can be considered a 'strategic business unit', which is useful for formulating category management strategies. In Figure 3, we illustrate our CCP scorecard based on two dimensions: the total value (sell-out, Euro) and the CCP of each category.

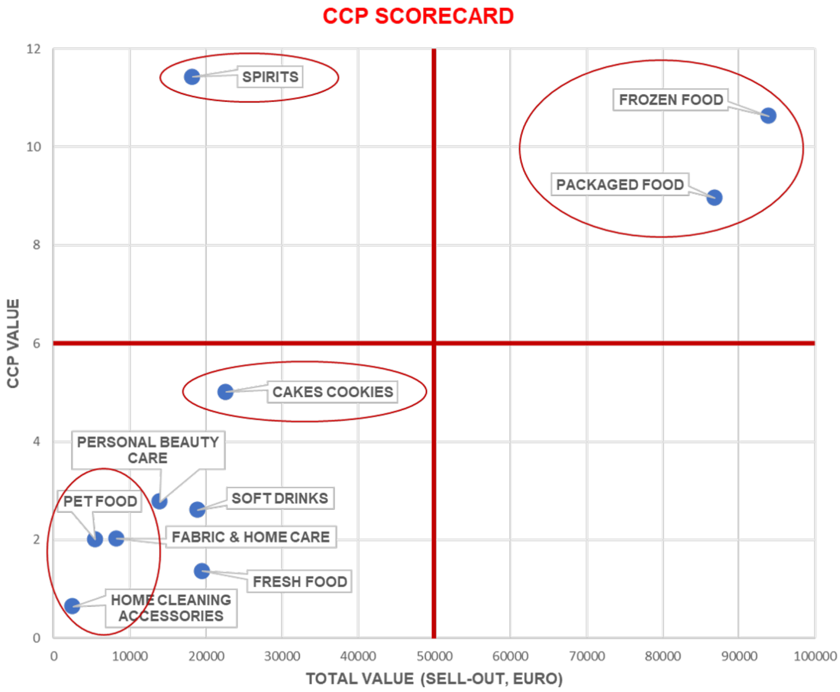

Figure 3: CCP scorecard

The scorecard based on the CCP (Figure 3) aims to identify the actual ability of each category to perform within the store, allowing professionals to make more effective strategic category management decisions. Considering the results illustrated in Figure 3, the 'Frozen Food' and 'Packaged Food' categories are the best-performing categories—those characterised by high sell-out and high CCP values. These are the less problematic categories because they can convert the high potential in terms of traffic in sell-out. Therefore, managers should continue to invest in these categories, capitalising on their high 'power' to convert traffic into sales (high CCP value). The categories 'Fabric home care', 'Home cleaning accessories', and 'Pet food' are the worst—those characterised by low values in both indicators. Considering their low ability to convert traffic into sell-out, managers could decide, for example, to move these categories towards the less strategic and low performance store areas, modifying the store layout. Above all, the scorecard allows professionals to better understand and manage the categories with low sell-out in absolute value but good (or excellent) performance in terms of CCP, such as the 'Spirits' category; considering the not-bad potential to convert traffic, managers could increase the number of shoppers visiting this category and/or the stay time to increase sell-out 'Spirits'. Looking only at the sell-out data and traffic data (GRP_i), managers may be led to think of disinvesting from this category; however, the CCP index is the highest, showing the very high potential of this category to convert the shopper flow into turnover. Hence, it could be considered a strategic category, and it could be very convenient to invest in some store marketing initiatives to increase the traffic flow and/or the time spent in category. ‘Spirit’ proved to be the category with the greatest conversion power but with a potential in terms of traffic flow still unexpressed compared to the average store potential. In this analysis, the necessity of an increase in the number of shoppers and in the stay time to obtain a given increase in sell-out was unexplored. Future studies are required in this sense. In any case, to determine which of the two strategies induces a greater increase in turnover, a category manager could test different category strategies, aiming to increase the traffic flow in the category (for example, through cross-promotions with other categories or by placing promotional material in the categories with the highest traffic to convey a greater flow in the category) and to increase the time spent in the category (for example, by placing communication merchandising material in category, such as free-standing display units, shelf edging, digital signage, posters, banners, etc.). It should not be surprising that there are no categories in the fourth matrix quadrant—those with high turnover in the presence of a low CCP—and that it is closely related to the CCP formulation. Indeed, the CCP is calculated by comparing the category sell-out volume with the GRP_i value, an expression of the category traffic volume. Therefore, for a low CCP value, there should be low sales performance compared to other store categories. If the sales and traffic volumes were equally high, we would have an average CCP value, as in low traffic volume and low sales performance. However, if the sales performance was high with low traffic, we would get a maximum CCP value (as for ‘spirit’ category). Therefore, the condition to obtain a low CCP value is necessarily the concomitant presence of high traffic volumes with poor sales performance or high sales performance but with a traffic volume (which is the denominator) tremendously higher than other categories (which is of course possible from a theoretical viewpoint, but improbable in reality, or related to an extremely specific situation). Obviously, it is necessary to talk about low, high, and medium performances of traffic or sales in a relative way by comparing the categories with each other within the same store over the same period.

9. Discussions

9.1. Theoretical implications

From a theoretical perspective, the paper contributes to the academic debate on the topic of category management and its impact on store performance Gooner et al. (2011); Dupre and Gruen (2004); Dhar et al. (2001); Gruen and Shah (2000). The study lays its foundations on the vision of CM adopted by Dupre and Gruen (2004) who consider each category within the store as a single strategic business unit. This approach is consistent with Desrochers and Nelson’s Desrochers and Nelson (2006) recommendations to retailers to change their focus from individual brands to overall product category performances. Starting from these assumptions, the paper proposes a new approach to category management performance measurement based on the combination of sell-out data with shopper behaviour data. Consistently with Desrochers and Nelson’s Desrochers and Nelson (2006) argument, the results show that sell-out data analysis alone is not sufficient to provide an adequate measurement of the performance of the single category and it could also be misleading for retailers. In this context, by using shopper behaviour metrics, the paper addresses the need of more comprehensive performance indicators Phua et al. (2015); Sorensen et al. (2017); Ferracuti et al. (2019); Larsen et al. (2020).Accordingly, the paper has identified a new key performance indicator, Category Conversion Power (CCP), which combines sell-out and shopper behaviour data sources. From a methodological point of view, the paper adopts RTLS technology M Paolanti (2017); Contigiani M (2016); Ferracuti et al. (2019); Sturari M (2016). The innovative techniques proposed, offer scholars and retailers' new measurement opportunities which, as stated by Boone et al. (2019), allow a greater convergence between the online and offline retail dimensions. Accordingly, the paper intends to contribute to shopper behaviour analysis in the physical retail sector.

9.2. Practical Implications

This paper provides several implications for retail managers, especially for those operating in the physical store sector. In fact, while the e-commerce purchasing process takes place entirely in the online environment and can therefore be easily monitored and measured, offline retail processes do not provide the same amount of data. In this sense, the work contributes to the consolidation of a data-driven approach that can be implemented thanks to the adoption of technologies capable of generating new data sources at support to retailers. Big data analytics can, overall, produce more exhaustive strategic insights than analysis based on single sell-out data or on direct observations of in- store shopper behaviours. Nonetheless, the proposed approach should not be considered as a replacement to the traditional analysis techniques at the point of sale but, instead, as either integrative or alternative. Existing approaches, as they are based on research methodologies such as direct observations, surveys, focus groups, laboratory-shops or "re- constructed" supermarkets, must recruit potential buyers in order to monitor their behaviours. By contrast, the proposed approach allows retailers to adopt a larger-scale vision that examines purchase paths and times of a much larger shoppers' sample. For example, in one day, the analysed technologies allow to collect data on the entire shopping path of hundreds of people. For stores of about 800-1000 sqm it is possible to register from 300 to 500 people per day, while, for hypermarkets of about 12,000 sqm, over 7,000 people. Furthermore, on the contrary of other approaches, as buyers are monitored unobtrusively, their behaviours are more likely to preserve authenticity. Nonetheless shoppers' privacy is always protected by the system retaining their anonymity. At the same time, equipping physical stores with technologies such as those used in this work, offers retail managers the possibility to connect the physical store with the digital environment, thus opening up new opportunities for omnichannel strategies. As stated above, the study focuses on CM by proposing a new CCP metric resulting from the combination of sell-out data with shopper behaviour data. Such integration allows retail managers to evaluate the performance of each single category in terms of conversion to purchase. The scorecard, presented as the main output, provides a clearer overview of the contribution of each category to the store. Figures 4 and 5 showcase an application example of the work's findings.

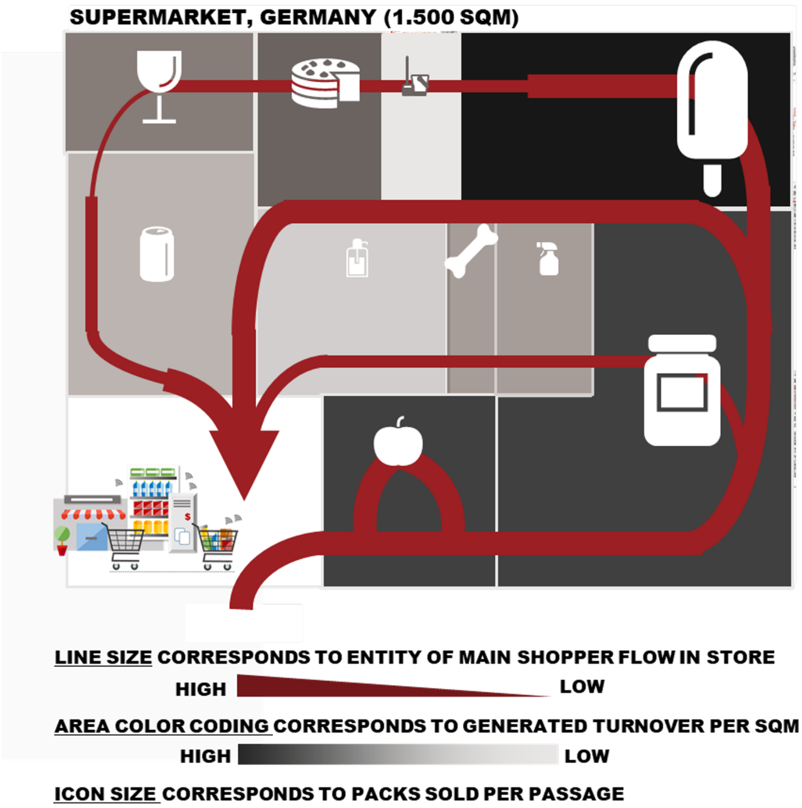

Figure 4: Representation of the store based on some parameters such as the amount of shopper flow in the store, the level of turnover generated per SQM and thenumber of packs sold per passage.

The integration of the generated data with the traffic flow data of each category, has allowed the creation of a diagram that clearly illustrates both the performance of each individual categories and the ways in which shoppers navigate them. As seen in figure 4, it was possible to create a store representation based on parameters such as the amount of shopper flow in the store, the level of turnover generated per SQM and the number of packs sold per passage. The "category performance map" can also be compared with the store heatmap (figure 5). The "hot" areas are represented in red and they correspond to the highest traffic areas. The "cold" blue areas are characterized by less traffic. Finally, it can be argued that the presented visualization approach, can support retail managers with a deeper awareness of what actually happens inside the store which can therefore be better interpreted with new information. Finally, through this approach, the effectiveness of the choices related to aspects such as store layout, merchandising, promotions, can be tested.

10. Conclusions

Retailing is one of the largest industries in the world and plays a central role in all countries' economy. In Europe, even when limiting oneself to grocery retailing, sales forecasts

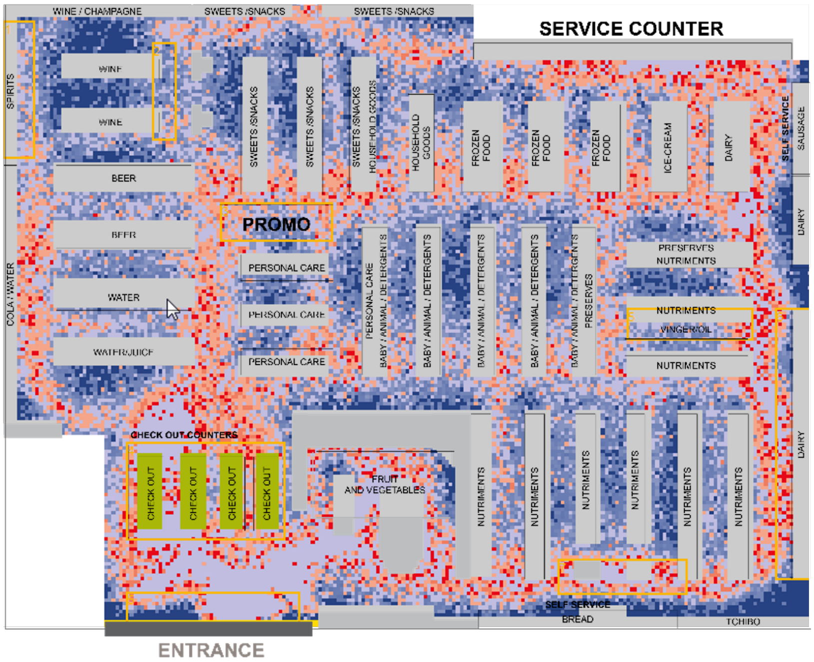

Figure 5: Store heatmap.

reach 2289 billion euros by 2022 (IGD, 2018), with millions of people employed in the sector. Given its size and ubiquity, research aimed to contribute to solving the challenges that retail is facing can benefit many stakeholders (Dekimpe, 2020) and counteract the 'Retail apocalypse', that is, the mass closures of many bricks-and-mortar retail stores, particularly in the United States (Peterson, 2017), partially due to the rise in online sales. Our work goes in this direction, showing how the opportunities of technology and big data can be exploited in improving the decision-making of retailers, and particularly CM decisions. This could help offline retailers gain competitiveness and improve performance. Based on the adoption of an RTLS-based system technology, we have generated useful shopper behaviour insights, which, combined with the sell-out data, can provide a more thorough assessment of the performance of single categories. Furthermore, the proposed approach led to the development of a new KPI – the CCP – that compares sell-outs across different categories, normalized according to the potential shoppers' traffic flow. This index provides information on the actual ability of each category to perform within the store; thus, it represents an effective basis for formulating effective CM decisions. We believe that the category scorecard can be adopted by retailers for discovering new patterns in data (Erevelles et al., 2016) alongside an analytics tool to make more accurate decisions, thereby improving both performance at the overall store level. In particular, the tool could be useful in supporting category managers in their decision-making processes regarding the following issues:

- to define an assortment planning following shoppers' needs and behaviours;
- to establish category's goals that are more coherent with consumer-related goals;

- to optimise retail space management, answering questions such as 'how much space to allocate to each category?' and 'where to place each category?';
- to identify new patterns and trends in shopping behaviours.

Answering these issues based on a true knowledge of shopper behaviour allows retailers to focus on their categories' investments to better identify merchandising strategies that could improve store performance (Begley and MacKenzie, 2018). Moreover, our research shows how retailers can exploit the potential of big data. In particular, we believe that shopper behaviour analysis could allow retailers to enrich their knowledge about both customers and store performance. From a managerial viewpoint, the acquisition of new data-driven knowledge resulting from the combination of multiple data sources (Bradlow et al., 2017), such as those of shopper behaviour and transactional ones, can guarantee retailers new sources of competitive advantage (Kumar et al., 2017; Grewal et al., 2017).

11. Limitations and directions for future research

This research presents some limitations related to both the technology/methodology and the validity of the results in other contexts. Although the sample was extremely large (dataset comprised 18,476 shoppers and a total of 85,449 SKU purchases analysed, equal to a turnover of €839,252.68), it referred to data coming from a single store. Thus, the results we obtained were strictly linked to the specific context (store format, location, shopper target, detection period) in which the data were collected, and more general observations of categories' performance could be made very carefully. However, this research contributes to the CM studies regarding how to measure category performance and not to evaluate the categories' performance. Another limitation is strictly linked to RTLS technology, which helps in detecting only the shoppers using a cart or a basket and, therefore, cannot consider all those individuals who make a short shopping trip or purchase few products without using a cart or a basket. The study also presents some limitations in relation to shoppers behaviour. As a matter of fact, the adopted technology allowed to understand how a shopper behaves within the store in terms of time spent, shopping journey and purchases. However, there are other factors that could also be taken into consideration. For example, previous studies recognized product price, perceived quality, brand awareness, time, seasonality, consumption frequency, after-sale services or guarantee, etc. as factors capable of influencing shoppers behaviour. The aim of this study is not to discover best practises in terms of category management or to understand each categories determinants to give general recommendations to professionals and researchers, but it is focused on uncover the potential of Big Data approach, combined with sales data to better measure category performances. For this reason, the store layout and planograms were the one given and were "fixed": it has not been made any changes during the study. In future researches we suggest to investigate more in detail the impact of planogram and layout changes on category performances, as suggested in the discussion section. Finally, a further limitation is the consideration of the shoppers sample as a single segment. In fact, times, shopping routes and money spent may vary depending on shoppers' age. In this regard, new possibilities for segmentation based on variables such as age, sex, but also sentiment, are in the process of being adopted thanks to the introduction of machine learning algorithms in the technologies adopted in the study. For future research, it would be interesting to repeat the study in different locations, types of store formats, and periods to verify the proposed scorecard's effectiveness in evaluating the categories' performance. Another interesting research stream could be to analyse the impact of decisions based on the proposed indicators. Our future work will focus on approaching retailing studies with a more holistic vision. In this sense, first, we are going to create and consolidate the connection between KPI and other factors determining purchase decisions. Second, as the adopted technologies are constantly evolving, there is a need to further validate them as scientific methods. This will result in the introduction of new variables which might improve the current understanding of purchasing behaviours. For example, for the one we analysed, the effectiveness of a store layout variation or of the merchandising material to convey traffic towards categories with high CCP values could be tested, monitoring how the performance regarding sell-out and CCP varies and verifying how the categories 'move' within the scorecard. Finally, this research proposes a first approach to study category performance, starting from data based on shopper behaviour analysis; future research should broaden the set of indicators than those proposed in this study to enrich the measurement framework.

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