The heterogeneity of shoppers' supermarket behaviors based on the use of carrying equipment[☆]

Nils Magne Larsen[a,*], Valdimar Sigurdsson[b], Jørgen Breivik[a], Jacob Lund Orquin[c,b]

[a] School of Business and Economics, UiT – The Arctic University of Norway, Havnegata 5, N-9405 Harstad, Norway
[b] School of Business, Reykjavik University, Menntavegur 1, Nauthólsvík, Reykjavik 101, Iceland
[c] Department of Management / MAPP, Aarhus University, Fuglesangs Allé 4, 8210 Aarhus V, Denmark

ARTICLE INFO

ABSTRACT

Research on in-store behavior has largely focused on shoppers with carts. In a study involving 15 stores and a total of 3540 shoppers, we document that only 20 percent of shoppers actually use shopping carts, while 28 percent use baskets and 51 percent use no carrying equipment. To better understand the role of carrying equipment, we collected data in a second study from 635 complete shopping trips using behavioral tracking technology and systematic sampling. We show that there is important heterogeneity in in-store behavior related to equipment and that carrying equipment is a suitable variable for segmenting shoppers. It is an objective and observable measure that consistently explains the variance in travel distance, shopping duration, store area coverage, walking speed, basket size, and shopper efficiency. We also find non-equipment trips to be least efficient, despite their popularity. The findings have implications for both research and retail practices.

1. Introduction

Academic research on what shoppers actually do in supermarkets is valuable but the handful of studies on shopper paths and in-store behavior is mostly restricted to shoppers using shopping carts with RFID tags on them. Supermarkets and small store formats have become increasingly attractive for shoppers – such as Walmart Neighborhood Markets, Target Express, and Tesco Express (Peterson, 2015; Statista, 2018), leading in general to less need for shopping carts or other in-store carrying equipment. Retail specialists report that shoppers worldwide generally tend to travel more frequently to grocery stores and also that they prefer to shop at small grocery stores to a greater extent than before (Nielsen, 2015; Scamell-Katz, 2004; Steiner, 2018).

To test this trend further, and to get more concrete figures, we systematically observed 3540 shopping trips to 15 different stores in five municipalities. Non-equipment trips represented the largest category of shopping trips overall and was shown to be widespread across all retailers and retail formats as 66.67 percent of the convenience store shopping trips involved no carrying equipment, 55.23 percent for discount stores, 46.25 percent for supermarkets, and 35.83 percent for hypermarkets. This points toward a problem as academic research on shopper paths and grocery buying behavior is mostly based on data from shoppers using shopping carts, meaning that short shopping trips

are likely to be under-represented and non-cart behaviors ignored. Since shoppers entering the store without any carrying device have been disregarded in earlier research, we know nothing about the behaviors associated with trips where the shopper chooses not to use any equipment. There is also limited knowledge on how trips involving a shopping cart deviate from those involving a basket.

Our approach is to look at the shopping trip as the unit of analysis, as the contribution includes a more holistic approach from around the beginning (choosing carrying equipment) to the end of a typical in-store experience (number of items purchased at checkout). Empirical research on key metrics of continuous streams of in-store behavior, such as store area coverage, shopping duration, and basket size, has laid the foundation for an empirically grounded shopper behavior theory (Sorensen et al., 2017), and has provided benchmarks for retailers as well as other stakeholders to apprehend in-store marketing performance. In the current paper, we introduce three new behavioral metrics: travel distance, walking speed and shopper efficiency, in the research literature. We argue that these three metrics contribute unique and important insight needed to document how shoppers on non-equipment trips behave compared to those using either a basket or a cart. While travel distance accounts for the shopper's effort along the entire shopping trip, average walking speed over the course of the shopping trip provides useful insight for determining shoppers'

attentiveness to in-store stimuli. Shopper efficiency, which in this paper is measured as purchases per meter travelled, complements the other fundamental behavioral metrics through its ability to acquire insight into how well the retailer serves various customer segments in terms of offering them an efficient trip. We show how such insight challenges widely used retail practices. In particular, we challenge the general assumption in the shopper marketing literature that an increase in shopper time or travel distance results in more opportunities to sell. As we argue, this depends on the shopper's walking speed. The higher the walking speed, the less attentive the shopper would be to in-store stimuli, thus leaving the retailer fewer opportunities to sell (unseen is unsold). Our data suggest that compared to other shoppers, those on non-equipment trips are less likely to be attentive to stimuli on their way to their in-store destinations.

Our data further show that the type of carrying equipment involved in shopping trips should not be ignored, neither in practice nor in research. There is important heterogeneity related to carrying equipment as the key shopper metrics (shopping duration, travel distance, store area coverage, walking speed, basket size, and shopper efficiency) differ across shoppers selecting different carrying equipment (no equipment, basket, cart). Carrying equipment is a suitable variable for segmenting shoppers. Type of equipment involved in a shopping trip is an objective and observable measure explaining a larger proportion of the variance in the behavioral metrics than, for instance, age and gender. In fact, it is the only variable in our empirical analysis that consistently explains the variance in key behavioral metrics. It is predictive in terms of occurring before the in-store behavior. It is therefore surprising that the choice of carrying equipment so far has not been used for behavioral segmentation (see Larsen & Sigurdsson, 2019).

We find non-equipment trips to be the least efficient, despite their popularity. This is an important input in the current discussion on retail disruption because shoppers deciding not to use any shopping equipment might be most vulnerable to new disrupting retail formats, such as grab-and-go stores and digital solutions, as their time and effort are not well spent. We provide evidence that knowing the proportions of shoppers selecting different types of carrying equipment (no equipment, basket, cart) can provide retailers with an important prediction of fundamental shopping patterns, transactional value, and vulnerability. The paper is organized as follows. In the next section, we give an overview of the relevant literature, followed by a description of our approach to data collection, measurements, and sampling. We then present the results of our study. The last section is concerned with discussion, conclusions, suggestions for further research, and managerial implications.

2. Carrying equipment and fundamental in-store behavioral patterns

Procedures for tracking in-store shopper behavior appeared in the marketing literature during the 1960s. An often cited example is Granbois (1968), who suggested a behavioral metric consisting of number of items purchased and the number of spots that the shopper passes in the retail store. At first, tracking was conducted mostly by means of researcher observation/shadowing, but since then, behavior tracking tools have changed immensely, with RFID tags attached to shopping carts in combination with antennas (receptors) being the most popular approach for tracking in-store behavior. However, other techniques have been used, such as RFID belts (e.g., Hui, Inman, Huang, & Suher, 2013), Bluetooth tracking from shoppers' mobile phones (e.g., Phua, Page, & Bogomolova, 2015), and as in this paper, video observation in combination with a tracking software, building on discrete in-store observations of shoppers.

Larson, Bradlow, and Fader (2005) were among the first to examine paths using the then new and exciting RFID technology on shopping carts. The procedures and findings were important for the establishment of an empirical science of shopping patterns as it could dispel a number of old assumptions and folklore. Their data showed the importance of the perimeter and that shoppers rarely weaved up and down all aisles. Shoppers tended to make short excursions into aisles rather than traversing the entire length, pointing to the importance of "colder" (such as middle aisles) and "warmer" areas (e.g., end-cap displays). This underpinned the need for more academic research into in-store marketing. Previously, in-store travel behavior had only been publicized from a basic foundation with applied methods in Underhill (1999) book "Why We Buy". Larson et al. (2005), on the other hand, scrutinized complete paths and found, based on multivariate clustering algorithm, that length of visit was important, leading to three clusters for short, medium, and long trips. The limitations found in their study were, however, that it included only studying shoppers using carts and not being able to predict shopper clusters with an objective variable. In this paper, we introduce an analysis of all types of shopping trips based on the objective choice of carrying equipment (including the choice of not using any equipment).

Our study contributes to the literature on the fundamental patterns of in-store shopper behavior (e.g., Hui, Bradlow, and Fader, 2009b; Hui, Fader, & Bradlow, 2009a; Hui et al., 2013; Sorensen et al., 2017) by examining and confirming fundamental heterogeneity of in-store behavior throughout the in-store shopping journey. To the best of our knowledge, studies reporting in-store behavioral data by using RFID, a tracking software or in-person observation either examine the shopping trip involving a regular shopping cart (e.g., Hui et al., 2009a, 2009b; Larson et al., 2005; Wagner, Ebster, Eske, & Weitzl, 2014) or do not report on the type of carrying equipment used (e.g., Hui et al., 2013; Sorensen et al., 2017). No studies examine the behavior of non-equipment users in particular and, therefore, we believe the empirical results from this study yield relevant insight for retailers as well as other stakeholders. We agree with Sorensen et al. (2017) that to advance the science of shopping (Underhill, 1999, 2009), it is important to use several key metrics each providing its own piece to the overall puzzle. We chose to go beyond store area coverage, shopping duration, and basket size (as introduced in paper by Sorensen et al.) to include walking speed, in-store travel distance, and shopper efficiency. We consider these to be suitable metrics for an empirical science of shopping and complementing those introduced by Sorensen et al. (2017).

In the following, we review relevant literature on in-store carrying equipment and the key behavioral metrics involved in the current study. Since there is little knowledge on carrying equipment and in-store shopper behaviors in general, we cannot derive explicit hypotheses from prior theory about the direction of effects for the different metrics.

2.1. In-store carrying equipment

The data presented in this paper show that different types of carrying equipment represent significantly different behaviors. We define in-store carrying equipment as any device offered by the retailer helping the shopper to convey items while shopping. Most store managers believe in the power of shopping baskets and carts to increase sales. The literature also recognizes this power (e.g., Cochoy, 2008; Grandclément, 2009). The most obvious result of shoppers' choice of carrying equipment is a physical constraint on the volume they can buy (Cochoy, 2008) and their freedom of movement in the store (Bogomolova, Vorobyev, Page, & Bogomolov, 2016; Larsen, Sigurdsson, & Breivik, 2017; Van den Bergh, Heuvinck, Schellekens, & Vermeir, 2016). Shoppers with no carrying equipment can move freely but can only buy what they can carry themselves. In line with this, the data from the current paper show that the choice shoppers make at the store entrance is associated with different average walking speed as well as number of purchases.

To the best of our knowledge, only three studies report behavioral data for more than one type of carrying equipment (Gil, Tobari, Lemlij, Rose, & Penn, 2009; Seiler & Pinna, 2017; Van den Bergh, Schmitt, &

Warlop, 2011). Gil et al. (2009) provide profiling data on patterns of shopper movement and behavior in a supermarket. They found many shoppers making short and medium trips and moving at a medium or fast pace. A short trip movement pattern was displayed by shoppers who tended to use baskets and not deep shopping carts; none of them were on a main shopping mission, and they spent limited time shopping. Prolonged shopping trips were mostly performed using a shopping cart. Using data collected from RFID tracking involving both shopping carts and baskets, Seiler and Pinna (2017) examined shoppers' search behavior in a physical retail store. Their findings show that carrying a basket rather than pushing a shopping cart significantly decreased search time. Van den Bergh et al. (2011) tracked shoppers in a hypermarket, from entry to exit, to examine behavioral differences between shoppers pushing a shopping cart versus those carrying a basket. They found that type of carrying equipment predicts whether a shopper will purchase vice products at checkout or not. They also found store visit duration to be significantly lower for basket users compared to cart users. Despite the limited number of studies, their results indicate that in-store behavior differs contingent on the type of carrying equipment shoppers use to assist them while shopping. We recognize that this stream of literature seems to neglect the behavior of non-equipment users.

2.2. Store area coverage

Store area coverage refers to the share of the total store area that shoppers traverse in their overall trip. The area that shoppers cover while shopping in a store plays an integral part in how in-store marketing stimuli will be received. Understanding how shoppers shop in a store and how they move around has been a focus for many researchers (Granbois, 1968; Scamell-Katz, 2012; Sorensen, 2016; Sorensen et al., 2017). Traditionally, it was believed that shoppers followed a methodical route up and down the store aisles covering the entire store (Hui et al., 2013; Larson et al., 2005). This is far from reality. Scamell-Katz (2012) found that while 25 percent of shoppers claimed they had been through the entire store during their shopping trip, less than two percent of that group covered more than half of the store. Sorensen et al. (2017) found shopping trips in large stores to cover a smaller proportion of the store (14% for hypermarkets) while trips in small stores covered a larger proportion of the store (i.e., 21% for small format stores and 30% for supermarkets). The challenges of understanding where shoppers go in a store has decreased with technologies such as RFID tags (Larson et al., 2005; Sorensen, 2016), but still there are challenges. Limitations to fixing RFID tags on carts and baskets are that it leaves out shoppers who choose not to use any carrying equipment, which could be an essential proportion of the shoppers visiting the store. Another limitation is that when shoppers leave their cart or basket to search for something, their behavior is unobservable (Sorensen et al., 2017). The shopper must hold on to the equipment at all times for us to have the data needed. While technological advancements have assisted researchers in understanding how people shop, the methodology still does not account for different shoppers and shopping styles, possibly leading to different results. As can be seen, for instance in Sorensen et al. (2017), the same store type, size, and country can still show a large difference in store coverage.

Sorensen (2016) describes three types of trips: quick, fill-in, and stock up. In his book, he describes a study where 75,000 shoppers from three stores were identified and categorized into these trip types. The study found that, on average, shoppers on quick trips visited 11.2 percent of the store, whereas fill-in shoppers and stock-up shoppers visited 21.1 percent and 41 percent of the store, respectively. Based on proprietary studies, Underhill (1999) found that the type of trip shoppers take determines their choice of carrying equipment. When shoppers enter a store, their choice of carrying equipment, or lack thereof, could be a descriptor of their trip type, but this is an academically underdeveloped area.

2.3. Shopping duration

Shopping duration refers to the total time spent in the store to complete an individual shopping trip. Shopping duration can be used to evaluate the level of shopper involvement (Sorensen, 2016), but best practice is to combine various metrics as shopping duration can also be related to inefficiency and shopper frustration. The time spent in the store is, for instance, related to store area coverage (and shopping trip type) as shown by Sorensen (2016); the more of the store visited, the higher the average shopping duration. Fill-in trips typically satisfy more urgent needs than stock-up trips and would thus generally involve less effort and time commitment (Kollat and Willet, 1967). Hui, Fader, and Bradlow (2009b) further note that grocery shoppers being goal directed (e.g. shopping with a list) probably exhibit different search behaviors than those without a clear set of purchase goals. Time pressure may also play a role in trip duration (Larsen & Sigurdsson, 2019), forcing the shopper to shop more productively, buying more items in less time (Bogomolova et al., 2016). Therefore, shopping trips involving the same proportion of the total store area can be quite different in terms of shopping duration. Combining store area coverage and shopping duration can as such give more detailed insights into shopping behavior – classifying shoppers as either "walkers" or more active shoppers based on the time they spend in various store areas (see a discussion of active shopping in Sorensen, 2016).

Like store area coverage, the introduction of technology such as RFID has made studying this metric all the easier. As mentioned earlier, applying such technology enabled Larson et al. (2005) to link trip duration to paths traveled in the store, finding that shoppers on shorter trips travel along the perimeter of the store and in the quick-convenience areas. Store layout, specifically the dominant path, can affect trip duration. Stores like Costco with their large dominant paths are capable of retaining shoppers in the stores for a long period of time as compared to stores that have many pathway options (Sorensen, 2016).

2.4. Travel distance

Travel distance can be defined as the length of the shopper's actual path in the store measured in terms of feet or meters. This is a metric that Hui et al. (2013) recently have used to study the effects of in-store path length on unplanned spending. Hui et al. (2009a) also use data on in-store travel to measure shoppers' travel deviations from the most optimal path (based on items the shopper actually purchase). Beyond this, few studies measure in-store travel distance, the main reason being, according to Hui et al. (2013), the difficulty of measuring path length. Researchers have concentrated on behavior that is easier to measure and correlate with path length. For instance, Granbois (1968) used number of aisles passed, while Sorensen et al. (2017) focus on store coverage as a proxy for path length. Although travel distance shares some similarity with area coverage, it does not replace it as a metric. Rather it complements it. While area coverage gives a perspective on how large a share of the total store area that a shopper visits, travel length demonstrates the extent of walking during the shopping trip. Disclosing only area coverage is not enough to account for a shopper's entire movements during the trip. Shoppers may visit the same area several times, or walk up and down some aisles in search of an item. Thus, travel distance reveals patterns that might be hidden in the rougher measure of area coverage. Although both metrics have been used to measure product exposure during a specific shopping trip, Hui et al. (2013) suggest that travel distance is a better measure of product exposure.

2.5. Walking speed

Walking speed is the distance covered during a certain period divided by the time taken to cover that particular distance. The three behavioral metrics discussed so far (store area coverage, shopping

duration, and travel distance) are all proxies for the extent to which shoppers are exposed to in-store stimuli along their shopping trip (e.g., product displays and in-store communication). However, visiting a store area is not the same as being influenced by stimuli in that area. A visit is an important prerequisite for influence; but for stimuli to trigger unrecognized needs and desires, or to trigger recollection of forgotten needs, requires the shopper's attention (Inman, Winer, & Ferraro, 2009). It is well known that shoppers spend a large proportion of their shopping time on intra-store travelling, visiting various store sections, where the perimeter serves as the main thoroughfare (Larson et al., 2005). We know only little about how much of this is "transit travel" where the shopper is just crossing to other store areas, walking faster (Larson et al., 2005), and is less likely to spend time shopping (Hui, Bradlow, & Fader, 2009c). Further, shoppers that perceive time pressure show less search activity in the store (Beatty & Smith, 1987); search time (in front of shelves) has also been found to be negatively correlated with average walking speed over the course of the shopping trip (Seiler & Pinna, 2017). Time pressured shoppers focus on getting to the store areas that carry categories that they plan to buy (Hui et al., 2009c), walking faster than normally (Helbing, Molnár, Farkas, & Bolay, 2001). As Seiler and Pinna (2017) argue, speed closely reflects a shopper in a hurry. Researchers and retailers have taken for granted that store area coverage and travel distance pay off in terms of un-planned purchases (Sorensen, 2016). This might prove to be correct for some types of shoppers using carts (the typical subject in shopper research), who might be on a stock-up mission (see Hui et al., 2009c; Kollat & Willett, 1967). The literature shows that walking speed is related to the choice of carrying equipment (Seiler & Pinna, 2017; Gil et al., 2009). Shoppers can "visit" many areas without actually perceiving much. Higher pace reduces the number of products that can be fixated in a given aisle, which affects the likelihood of making un-planned purchases. Average walking pace must be taken into account along with the other key metrics to better understand shoppers' search activity and attentiveness to stimuli along the entire in-store path. The metrics therefore make more sense when combined rather than considered in isolation.

2.6. Basket size

Basket size is the total number of items that the shopper purchases on a given shopping trip. Basket size is a key indicator for success when it comes to retail marketing performance. Shoppers' goals affect in-store behavior (Bell, Corsten, & Knox, 2011; Kollat and Willet, 1967) and trip type and basket size tend to go hand in hand. Therefore, the increasing practice of quick trips has entailed decreased basket sizes. Most shopping trips end in fewer items purchased than ever before (Sorensen et al., 2017). This trend has made more shoppers refrain from using any kind of carrying equipment enabling quick entry and exit (Larsen et al., 2017). Cultural differences also come into play when it comes to basket size. Some countries have a daily-shopping, quick-trip culture, while others may be more inclined towards stock-up trips – each with very different basket sizes and therefore carrying equipment needs (Scamell-Katz, 2012). There is a need for a clear and objective classification of shoppers – possibly based on the objective measure of choice of carrying equipment.

2.7. Shopper efficiency

The term efficiency is generally associated with the ability to accomplish something with the least waste of time and effort (Atkins & Kim, 2012). Time and effort are non-monetary sacrifices consumers must make in the exchange with the retailer and that affect shoppers' perceived value (Inman & Nikolova, 2017). From this perspective, shopper efficiency refers to consumers' actual performance compared with what they can achieve with the same consumption of non-monetary resources. Shoppers would as such be more efficient if they solved

a given shopping task using less input in terms of shopper seconds (Sorensen, 2009, 2016; Bogomolova et al., 2016) or in-store travel (Larsen, Sigurdsson, Breivik, Fagerstrøm, & Foxall, 2019). The importance of efficiency has increased in shopping situations (Davis & Hodges, 2012), resulting in consumers demanding more convenience and effort-saving solutions from retailers (Nielsen, , 2014). From a retailer perspective, research indicates that shopper efficiency has a positive association with total store sales (Sorensen, 2009).

Prior literature examines efficiency either from a per dollar/item perspective (Bogomolova et al., 2016; Sorensen, 2009; Davis and Bell, 1991) or from a path perspective (Hui et al., 2009a). To date the per-dollar/item perspective draws exclusively on shopping duration as the non-monetary sacrifice. Sorensen (2009) uses observations of more than 100,000 shopping trips in the United States to examine the relationship between seconds per dollar (how fast shoppers spend) and store sales. Davies and Bell (1991) examine average expenditure per minute and the average number of items purchased per minute over the entire shopping trip. Bogomolova et al. (2016) propose an approach in measuring shopper efficiency that includes a "per-item shopping time" measure focused specifically on the purchasing tasks in the store (the time spent purchasing one item, including approaching the shelf, considering available options and making the purchasing decision). On the other hand, the path perspective involves a greater focus on "excessive walking", such as deviances from the most optimal in-store path, leading to more walking (more effort) than necessary to acquire the items wanted. For instance, Hui et al. (2009a) compare consumers' actual in-store path with the most efficient path based on items of the purchase.

Better access to in-store behavioral data, such as travel distance, has opened up new opportunities in measuring shopper efficiency. Since travel distance reflects the number of feet/meters the shopper travels in the store to acquire items, it accounts for the shopper's effort along the entire shopping trip compared to shopping duration in a better way. Travel distance is also less sensitive to in-store behaviors not related to acquiring items, such as when shoppers stop to spend time chatting with other shoppers or on the phone (see Larsen et al. [2017] for a categorization of basic behaviors occurring in a retail store). Finally, certain types of carrying equipment, shopping carts in particular, decelerate shoppers delaying those who want to shop as fast as possible (Larsen et al., 2017; Larsen & Sigurdsson, 2019). Type of carrying equipment involved in a shopping trip may therefore influence time-based efficiency measures directly, while having no direct effect on measures based on travel distance. Travel distance is therefore a more valid replacement for shopping duration in the efficiency equation. Although the present knowledge on how travel distance-based shopper efficiency should be measured is limited, it is logical to connect in-store travel distance with basket size (e.g. purchases per feet/meter travelled or distance travelled per item purchased). This would indicate how efficient each feet/meter travelled is for the shopper.

3. Method

3.1. Study 1

In order to determine the prevalence of non-equipment trips in grocery retailing, the objective of Study 1 was to examine, across different grocery stores, store formats, and grocery segments, the proportion of shoppers selecting either a shopping cart or a basket when entering the store. This study was conducted in three cities and two communities in Norway and included 15 grocery stores belonging to different retailers, retail formats and retail chains. 240 observations were made at the entrance of each store, and the observations were distributed equally between three time slots (08:00–10:00; 10:30–12:30; 15:00–17:00) and equally between Monday, Wednesday, Friday and Saturday.

The total sample consisted of 3540 observations. Using a systematic

sampling process, we chose a random starting point and then picked every fifth shopper entering the store for our sample (Malhotra & Birks, 2007:416). For each grocery store, we checked the availability of different types of carrying equipment (carts and baskets) and whether or not the store had cart locks. We used a structured observation guide.

3.2. Study 2

Research objective. The objective of Study 2 was to examine entire shopping trips in a typical grocery store to determine how non-equipment trips differ from trips involving either a basket or a shopping cart on key behavioral metrics.

Data and data collection method. We collected data from one major retail chain soft discount store during the period of March to October 2016. The store was located in a suburban area of a Norwegian city. The store had a sales area of approximately 1200 m², it carried an assortment of 5500 stock-kept units (SKU) and its layout resembled that of most other supermarkets of this size. We used a system of Wi-Fi cameras and tracking software to collect in-store behavioral data from individual shopping trips. The cameras covered the entire sales area and were used to observe shoppers' movements in the store and where and when shoppers picked an item from a shelf or a display. Shoppers' arm and hand motions reveal much information about their interaction with items and the purchase of items (Liu, Gu, & Kamijo, 2017). In our study, an item purchase is an item observed, picked by the shopper from a display or a shelf and not returned to the display/shelf. We applied the same tracking software and procedures as Larsen et al. (2017). The interface of the tracking software represented the store layout but was down-scaled to fit a computer screen. The pattern of movement and item pick-ups were fed into the tracking software in real time. We refer to Larsen et al. (2017) for details on the functionality and interface of this software, which type of data it registers automatically, and the procedures for feeding real-time observational data into the software. The advantage of camera-based observations in combination with tracking software is that shoppers' natural shopping experience is uninterrupted since there are no interventions during the shopping trip.

Targeted shoppers' entire shopping trips were observed, one-by-one, from their point of entry and all the way to the checkout. Entry time was marked by the shopper picking up an in-store carrying equipment (or choosing not to use one) and crossing a predefined spot at the beginning of the shopping trip. We used two predefined entry points, one at the main entrance that most shoppers cross to approach the first zone displaying items, and a second at the checkout for those shoppers taking a shortcut through the space between the cash registers. Our exit time measure was the exact moment when a shopper would place the first item on the checkout belt (if there is no queue), or the moment when the shopper joined the queue. This excludes time spent queuing (which depends on whether there is a queue or not), and time at the checkout involving barcode scanning, which is dependent on basket size (see Bogomolova et al., 2016). While a system consisting of RFID tags (on baskets and/or shopping carts) and antennas is unable to perfectly identify the start and end of every shopping trip (Hui et al., 2009c) and captures data only from equipment users, our approach overcomes these shortcomings.

We fed demographic data (gender and age) and the shopper's choice of carrying equipment into the tracking software immediately after the completion of the shopping trip. Two researchers were involved in tracking each of the shopping trips. As shopper interventions were precluded, we estimated age and gender based on visual inspection of the real-time images provided by the Wi-Fi cameras; we particularly scrutinized the shoppers' face, hair and body shape.

Dependent variables. The entire store was divided into 85 store areas based on product categories. We operationalized travel duration as the time it takes to complete the shopping trip, from the point of entry to the exit point (measured in minutes). Travel distance was operationalized as the number of meters travelled from the point of entry to the exit point. Store area coverage was operationalized as the number of store areas visited divided by total number of store areas. Walking speed (meter per second) was operationalized as travel distance divided by shopping duration (converted into seconds), and basket size was operationalized as number of purchased items from the point of entry to the exit point. Finally, shopper efficiency was operationalized as basket size divided by travel distance.

Independent/control variables. Age, carrying equipment, type of shopper, shopping period and shopping time are dummy variables. We categorized age into seven age groups, and carrying equipment into three types (no equipment, a basket or a shopping cart). The basket type include shoppers using either a small hand-held basket or a larger basket with wheels. Four types of shoppers are predefined in the tracking software: male, female, family or group. Thus, gender only applies to individual shoppers in the dataset. Shopping period refers to weekday or weekend, where weekend reflects the period from Friday at 12:00 and throughout Saturday (store is closed on Sunday). Finally, we split shopping time into peak and off peak shopping time, where peak shopping time represents the period from 12:00 until 18:00, whereas the remaining opening hours represents off-peak shopping time.

Sampling approach. We split the opening hours as well as weekdays and weekends into strata, and we used the store's entire traffic pattern for February of 2016 (derived from a traffic counter we placed at the entrance) to determine the total number of shopping trips to target in each strata (proportionate stratified sampling). We designed a plan for the data collection, including which strata to target when. The selection of shoppers for tracking (within a selected strata) was based on the rule of choosing every fifth shopper entering the store. We tracked a total of 635 shopping trips, 522 of which were individual shoppers (272 male and 250 female). We used a sign at the entrance of the store to inform shoppers about observational activities involving the use of Wi-Fi cameras, and we notified the appropriate authorities prior to the study.

4. Data analysis

This section reports on the results from the two studies separately. We start by presenting shoppers' carrying equipment choice frequencies based on data from Study 1. Then, we present the results of Study 2. By means of several sets of linear regressions, we offer further insight into fundamental behaviors connected to type of carrying equipment.

4.1. Results – Study 1

Study 1 was conducted to detect how widespread non-equipment trips are in grocery retailing. The results from in-person observations at 15 stores of different retail formats are shown in Table 1. We have also added comparable statistics from our Study 2 to this table. Note that

Table 1
Shoppers' choice of carrying equipment across retailers and store formats.

Retail format	No equipment	Carrying equipment		Total
		Basket	Cart	
Convenience store	320	90	70	480
	66.67%	18.75%	14.58%	100%
Discount store	1296	790	494	2580
	50.23%	30.62%	19.15%	100%
Supermarket	111	84	45	240
	46.25%	35.00%	18.75%	100%
Hypermarket	86	41	113	240
Total	35.83% 1813	17.08%	47.08% 722	100%
	51.21%	1005	20.40%	3540
		28.39%		100%
Study 2 (A discount store)	270	252	113	635
	42.52%	39.69%	17.80%	100%

two of the stores in Study 1, one discount store and the hypermarket, had cart locks. These two stores represent 13.5 percent of all observations in Study 1.

As shown in Table 1, shoppers' most frequent choice in three out of four retail formats is no equipment. Although the most frequent choice in hypermarkets is a shopping cart, the data demonstrate that non-equipment and basket use also is rather common.

4.2. Results study 2

4.2.1. Carrying equipment and in-store behavior

Frequency statistics reported in Appendix 1 show sample characteristics by choice of carrying equipment. Of the 635 shopping trips studied, 42.5 percent involve no carrying equipment, while 39.7 percent and 17.8 percent of the trips involve a basket or a shopping cart, respectively. For the 522 shopping trips carried out by individual shoppers only, 43.9 percent of the trips involve no equipment, while 40.8 percent involve a basket and 15.3 percent involve a shopping cart.

Table 2 reports average statistics on the six key behavioral metrics (See Appendix 2 for a correlation matrix). The data in Table 2 indicate that the key behaviors vary widely by choice of carrying equipment. As an example, average walking speed doubles for non-equipment users relative to those using a cart. Further, the data indicate that shopping duration is more than four times longer for cart users relative to non-equipment users. Moreover, store area coverage for cart users is about double that of non-equipment users.

To examine the heterogeneity of key in-store behaviors, we performed linear regressions using OLS. The independent variables were gender, age, type of carrying equipment (including no equipment), basket size (but not included where it is modeled as the dependent variable), shopping period (weekday or weekend) and shopping time (peak/off peak). Model development and decision on the model employed were based on best overall fit assessed by Akaike information criterion (AIC) and Schwartz Criterion (BIC) on the behavioral metrics. Due to heterogeneity in the estimated models, we report robust standard errors based on the Huber/White estimate of variance. In this analysis, families and groups are disregarded as classifying them through observation is inflicted with potential for bias; therefore only cases involving individual shoppers are included. In addition, one observation is removed based on measures of leverage assessed by DFBETA and Cook's D. Thus, the final sample consists of 82 percent of the total sample, or 521 complete shopping trips. Table 3 reports unstandardized regression estimates for the five dependent variables representing the key behavioral metrics. We have tested for multi-collinearity by calculating the variance inflation factor (VIF) and find the levels to be below the frequently used threshold of 5.

To ease interpretation of the estimated coefficients, the constant term of the linear regressions reported in Table 3 has been suppressed into the coefficients representing no equipment. Thus, the coefficients for no carrying equipment represent values with reference to the baseline for the control variables: age, gender, shopping period, shopping time, and zero purchases (regression 1 through 4 in Table 3).

The OLS results indicate that cart users, basket users and non-equipment users exhibit different in-store behaviors. Our estimates demonstrate that shopping duration, walking speed, travel distance, store area coverage, and basket size (number of items purchased), all return significant coefficients for all categories of carrying equipment. In addition, tests of joint equality in carrying equipment coefficients indicate these to be different from each other for all specified models (at $p < 0.01$, while $p < 0.05$ for shopping duration). The importance of carrying equipment in explaining the variance in the in-store behaviors is further substantiated by tests implying that removing carrying equipment would reduce R-square and increase AIC/BIC. This implies that carrying equipment enhances model fit beyond what may be inferred from demographics, shopping period and shopping time alone.

Further inspection of Table 3 implies differential effects of age and

gender on the behavioral metrics. For instance, age and gender are not significantly related to travel distance, and only gender ($p < 0.001$) and the oldest age category ($p < 0.01$) are associated with shopping duration. Walking speed refers to number of meters covered per second, representing the shopper's average walking speed throughout the shopping trip. Our estimates demonstrate that walking speed decreases when choosing a basket; a further decrease happens when using a shopping cart, both relative to no equipment. Further, the estimates imply that increased age is associated with lower walking speed and that the walking speed of females is slower than that of men.

Our estimates further suggest that weekend shopping is linked to area coverage ($p < 0.05$), indicating that in this period shoppers visit a smaller percentage of the total number of store areas. Moreover, weekend shopping trips seem to include more items as basket size increases by 0.97 units on average. Further, peak-hour shopping impacts area coverage ($p < 0.01$) by an average of 1.26 percent increase in store areas visited.

The estimated models vary in explaining the variance in the observed data, ranging from 73.8 percent to 94.0 percent. Choice of carrying equipment together with basket size are the only explanatory variables among those tested that consistently contribute to explaining the variance of the five behavioral metrics. This research does not study causality but shows instead that carrying equipment, age, gender, weekend shopping, and peak hour control for and can be used to capture the heterogeneity in the key behavioral metrics, suitable for behavioral segmentation and new managerial insights.

We also conducted OLS estimations with robust errors to extract coefficient estimates on in-store shopper efficiency. We measured in-store shopper efficiency as basket size divided by travel distance, which expresses how efficient the shopper is in terms of purchases per meter travelled. Table 4 reports the regression estimates. Similar to Table 3, the constant term in Table 4 has been suppressed into the coefficient representing no equipment.

The unstandardized regression estimates reported in Table 4 indicate that shopping trips involving a cart, a basket or no equipment, on average, exhibit a significant association ($p < 0.001$) with in-store shopper efficiency. The coefficient estimates imply that non-equipment trips are the least efficient, while shopping trips involving a cart are most efficient. Table 4 further indicates that efficiency decreases with the increase of shoppers' age, while neither weekend, peak shopping hours, nor gender are related to better or poorer shopper efficiency.

5. Discussion, conclusions and managerial implications

In this section, we first discuss the key findings related to carrying equipment for each behavioral metric. This is followed by a short discussion of the control variables. We then present the main conclusions before discussing managerial implications and limitations.

5.1. Discussion

5.1.1. Store area coverage

Store area coverage was 19.62 percent on average. This is similar to the findings on store coverage presented in Sorensen et al. (2017), where they found that shoppers covered 21 percent of the small store formats.[1] Sorensen et al. (2017) have shown that most shoppers tend to cover a small proportion of the store, and that they shop quickly and only purchase a few items. The current research can be classified in a

---

[1] Their smaller store formats consist of 200–300 m², while our store is a soft discount store, located in Norway and around 1200 m². Sorensen et al. (2017) have shown that findings tend to generalize between countries (USA, UK, China, and Australia), most store formats (supermarkets, hypermarkets, convenience, and specialty stores), and store sizes (from 200 m² to 19.000 m²). We here add to that generalization.

Table 2
Descriptive statistics of in-store behavior by choice of carrying equipment.

Variable	No equipment		Basket		Cart		Overall	
	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.	Mean	Std. Dev.
Average walking speed (m/s)	0.60	0.27	0.45	0.17	0.30	0.11	0.49	0.24
Travel distance (m)	94.95	43.05	159.38	63.29	214.38	103.07	141.77	79.03
Shopping duration (min)	3.30	2.26	7.05	4.19	13.43	8.45	6.59	5.90
Basket size	2.21	1.41	6.58	3.61	14.06	8.91	6.06	6.15
Store area coverage (%)	14.23	5.72	22.04	6.18	27.12	7.72	19.62	8.02
Shopper efficiency	0.026	0.015	0.042	0.019	0.065	0.027	0.039	0.024
N	270		252		113		635	

Table 3
In-store behavior estimates.

Dependent variable	Shopping duration (min)			Walking speed (m/s)			Travel distance (m)			Area coverage (%)			Basket size		
Carrying equipment															
No equipment	1.452	(2.91)	**	0.768	(12.66)	***	76.62	(8.20)	***	11.57	(9.99)	***	1.139	(2.95)	**
Basket	2.255	(3.75)	***	0.675	(10.56)	***	98.39	(8.68)	***	15.66	(11.99)	***	5.562	(11.05)	***
Cart	2.673	(3.30)	**	0.651	(9.55)	***	75.20	(5.48)	***	13.51	(8.66)	***	12.72	(12.04)	***
Age															
0–20[1]															
21–30	−0.578	(−1.02)		−0.066	(−1.06)		−8.119	(−0.74)		0.189	(0.15)		1.128	(2.59)	**
31–40	−0.441	(−0.78)		−0.109	(−1.74)		−11.13	(−1.02)		−0.315	(−0.24)		0.602	(1.39)	
41–50	−0.171	(−0.28)		−0.110	(−1.80)		−1.410	(−0.13)		1.004	(0.77)		0.924	(1.66)	
51–60	−0.018	(−0.03)		−0.132	(−2.11)	*	−4.424	(−0.37)		0.406	(0.30)		−0.603	(−1.15)	
61–70	1.094	(1.82)		−0.168	(−2.69)	**	−5.842	(−0.53)		0.291	(0.23)		−0.676	(−1.24)	
71 +	2.704	(3.01)	**	−0.240	(−3.53)	***	21.15	(1.43)		3.918	(2.61)	**	−1.950	(−1.95)	
Gender															
Male[1]															
Female	0.990	(3.78)	***	−0.0917	(−4.97)	***	−0.425	(−0.09)		0.0963	(0.20)		0.225	(0.62)	
Basket size	0.632	(14.98)	***	−0.0108	(−5.51)	***	9.661	(14.16)	***	0.876	(14.30)	***			
Shopping period															
Weekday[1]															
Weekend	−0.379	(−1.38)		0.0369	(1.82)		−6.475	(−1.45)		−1.078	(−2.29)	*	0.968	(2.26)	*
Shopping time															
Off peak[1]															
Peak	0.187	(0.72)		0.0043	(0.24)		8.581	(2.01)	*	1.259	(2.70)	**	0.517	(1.39)	
R²/adj.R²/Prob > F	0.865	0.861	***	0.869	0.866	***	0.905	0.903	***	0.940	0.938	***	0.738	0.732	***
AIC/BIC	2608.2	2663.6		−149.5	−94.1		5538.9	5594.3		3204.7	3260.1		2973.5	3024.6	

* p < 0.05, ** p < 0.01, *** p < 0.001, [1] = base, t statistics in parenthesis, N = 521, OLS with robust errors

similar vein, working on the empirical generalization of in-store shopping behavior contrary to armchair theorizing. Our results are in the same direction for short trips, and we operationalize them as "non-equipment" shopping to avoid any possible tautology or forced outcomes ("small trips leading to small shopping"). While Sorensen et al. (2017) focused on store area coverage between different store formats and store sizes, the current study demonstrates that there are also important differences between shopping trips within a store, where choice of carrying equipment can be used as a behavioral segmentation. Our results showed that the largest consumer group, non-equipment shoppers representing 42.52 percent of the total number of shoppers, only visited on average 14.23 percent of the store, meaning that the largest consumer group did not visit over 85 percent of the total store area. The other types of shopping trips cover more of the store but still ignore most of the areas. Those using a basket covered on average 22.04 percent, and the smallest segment, cart users covered on average 27.12 percent of the store, implying that most of the store is currently irrelevant to the shopper, with no opportunity to sell. This adds to the literature and managerial discussion on the recent changes happening in shopping trips and paths and has clear implications for the literature on shopper behavior and the possible contribution of in-store marketing. Larson et al. (2005) introduced the expediency of equipping shopping carts with RFID tags for shopper research. They profiled

shopping paths based on zones visited and showed, contrary to conventional wisdom, that shoppers did not tend to weave up and down the aisles. The current research adds data on non-equipment use and shows that the use of carrying equipment can also be used to profile different shopping trips as the findings generalize across the in-store behavioral metrics, including store area coverage. Data on shopping trips not involving any carrying equipment are valuable as they have been seriously underrepresented in previous studies.

5.1.2. Shopping duration

The average shopping duration was 6.59 min, a finding that is in line with many retail specialists reporting decreased store-shopping willingness and increased emphasis on "grab and go" shopping (Nielsen, 2015; Scamell-Katz, 2004; Steiner, 2018). This average shopping duration is similar to the mean value Sorensen et al. (2017) reported for small format stores (5 min) and the main conclusions are the same. Although the main contributions are on a different level, our results also show that most shopping trips are short. Sorensen et al. (2017) show an inter-store heterogeneity of key behavioral measures, while the current research reveals intra-store heterogeneity based on shoppers use of carrying equipment during the consumer journey. This is an important addition to the literature as the limited research on how shoppers actually act in stores in terms of shopper paths and in-store

Table 4
Shopper efficiency estimates.

Dependent variable	Shopper efficiency (Basket size/Travel distance)		
Carrying equipment			
No equipment	0.0203	(8.25)	***
Basket	0.0364	(12.35)	***
Cart	0.0610	(14.02)	***
Age			
0–20[1]			
21–30	0.00924	(3.25)	**
31–40	0.00676	(2.30)	*
41–50	0.00482	(1.66)	
51–60	0.000335	(0.10)	
61–70	−0.00125	(−0.40)	
71 +	−0.0106	(−2.29)	*
Gender			
Male[1]			
Female	0.000348	(0.21)	
Shopping period			
Weekday[1]			
Weekend	0.00265	(1.52)	
Shopping time			
Off peak[1]			
Peak	0.00106	(0.63)	
R^2/adj. R^2/Prob > F	0.828	0.824	***
AIC/BIC	−2653.4	−2602.4	

* $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$, [1] = base, t statistics in parenthesis, N = 521, OLS with robust errors

behaviors has mostly been restricted to shoppers using shopping carts fitted with RFID tags. This can lead to a significant overestimation of shopping time, under-representation of short shopping trips and unawareness of instances during the shopping trip when the carrying equipment is not actively used, or when it is not used at all. Larsen, Bradlow and Fader (2005), for instance, noted that the data included a number of long shopping paths (up to 6 h) that most likely did not consist of actual shopping behavior. As a consequence, they excluded all paths lasting more than two hours. The current findings reveal substantial differences in shopping duration based on the shoppers' choice of carrying equipment. Shopping trips involving no carrying equipment lasted on average 3.30 min, while those involving either a basket or a cart took on average 7.05 min and 13.43 min to complete, respectively. These results support previous research findings pointing towards shorter duration for trips involving baskets rather than carts (Van den Bergh et al., 2011; Gil et al., 2009). Larsen and Sigurdsson (2019) put forward a conceptual framework on research on in-store carrying equipment in terms of antecedents and consequences. Their literature review reveals that consumers have a "shopping time budget", where available time and the opportunity cost of time could be linked to the choice of carrying equipment, taking retailers from psychographics over to a more manageable segmentation through a simple behavioral choice. Furthermore, the current research adds to the literature in terms of data on the most frequent and quickest shopping trips: those performed without any carrying equipment.

5.1.3. Travel distance

The average travel distance for all shopping trips was 141.77 m. The findings demonstrate that carrying equipment is associated with how many meters shoppers cover. While non-equipment users travelled on average a distance of 94.95 m, basket users and cart users travelled on average 159.38 m and 214.38 m, respectively. This suggests that non-equipment users take shorter trips within the store compared to both basket and cart users, which limits their exposure (opportunity to see) to in-store stimuli. Although there is some evidence in the literature suggesting that shoppers on shorter trips use more baskets while those on longer trips mostly use a shopping cart (e.g., Gil et al., 2009), the

current study is the first to systematically examine how shoppers' actual travel distance is linked with type of carrying equipment. Besides providing meaningful information on shoppers' exposure to products, travel distance also provides valuable input to the shopper efficiency equation.

5.1.4. Walking speed

Walking speed is a relevant behavioral metric because increased pace can have a negative effect on shoppers' attention to stimuli along their in-store paths. The average walking speed for all 635 observations was 0.49 m per second (m/s), and the analysis shows that carrying equipment is associated with average walking speed over the course of the entire shopping trip. Non-equipment users walked on average twice as fast as shoppers pushing a shopping cart (0.60 m/s versus 0.30 m/s), and basket users had a pace in between (0.45 m/s). One explanation for non-equipment users walking fastest could be that their passage through the store is less impeded (Larsen et al., 2017; Wagner et al., 2014), and that they are less likely to spend time searching. For instance, due to the size of a shopping cart, cart users tend to be deaccelerated when maneuvering it in the store, such as when turning corners, due to the worry of bumping into other carts or shoppers. Cart users can also easily get stuck behind other cart-users and thus, experience a slower pace in parts of their shopping trip (Larsen et al., 2017). Seiler and Pina (2017) show that basket users are less likely to search than cart users and that they as such exhibit a higher average walking speed. Following those lines, non-equipment users are even less likely to be on the lookout for products. They know exactly which few items they want, in which areas these are placed, and they have no carrying equipment slowing them down on their beeline to these few items. Our findings are in line with the few studies displaying data on how shoppers with baskets and carts deviate in terms of walking speed (Seiler & Pinna, 2017; Gil et al., 2009), and we contribute to this scarce literature by adding insights on non-equipment users in this respect.

5.1.5. Basket size

The average basket size across the 635 shopping trips was 6.06 items, which reflects the presence of many shopping trips where shoppers purchase a relatively small number of items. This is in line with Sorensen et al. (2017) who found a consistent pattern across formats and countries involving fewer than ten purchased items on most shopping trips. Our findings also point to considerable differences in average basket size when shopping trips are segmented on the basis of carrying equipment. The largest group, non-equipment shoppers, purchased on average 2.21 items, meaning that most shoppers only bought a few items. On the other hand, shoppers carrying a basket or pushing a cart purchased on average 6.58 items and 14.06 items, respectively. The large group of non-equipment shoppers with limited basket sizes challenges existing retail principles, including store layout and in-store tactics to increase unplanned purchases.

5.1.6. Shopper efficiency

Our data show that non-equipment shoppers have the lowest efficiency among all shoppers in terms of purchases per meter (p/m) travelled (0.026 p/m for non-equipment trips, 0.042 p/m for basket users and 0.065 p/m for cart users, on average). We attribute this mainly to store layout, which follows design principles that most grocery stores have drawn on for decades (see Granbois, 1968). The characteristics are a grid layout with a main thoroughfare on the outside edge of the aisles and popular product categories located around the store to encourage consumers to walk longer distances and thereby to pass many other products on their way. Such a store layout forces non-equipment shoppers to walk through the entire store despite their few needs, spending more time and effort than necessary. The larger the store, the more inefficiency for non-equipment shoppers in particular.

Because Hui et al. (2009a) merely treat store layout as a fixed parameter in their analyses, their approach to measure efficiency would

not identify the type of inefficiency we detect in our study. As such, Hui et al. (2009a) do not discuss the extent to which the most optimal path in itself is inefficient for some group of customers. Their finding that longer shopping trips with a larger basket size and a longer shopping durations are least efficient (most deviation from the optimal path), is therefore not necessarily contradictory to our findings.

5.1.7. Control variables

In the current study, carrying equipment is the only independent variable that consistently contributes in explaining the variance in all of the six behavioral metrics. Gender, shopping time and shopping period, each contributes in explaining the variance in only two of the six metrics. Gender is only associated with shopping duration and walking speed. Shopping period is only associated with basket size and store area coverage, and shopping time is associated with only travel distance and store area coverage. Furthermore, the results imply differential effects of age on the six behavioral metrics. For instance, age is not associated with travel distance, and only the oldest age category is associated with shopping duration and area coverage. Type of carrying equipment (or the absence of one) involved in the shopping trip should therefore not be overlooked in research examining shoppers' in-store behaviors.

5.2. Conclusions

An emerging empirical literature built on technological innovations to study consumers' actual behavior in retail stores has shown generalizable patterns related to key behavioral metrics, describing the heterogeneity of shopping trips across retail outlets, formats, and countries. We repeat similar analyses and broaden the exploration of fundamental in-store patterns by adding three additional metrics: travel distance, walking speed, and shopper efficiency. These new measures complement those proposed by Sorensen et al. (2017) as they lead to better documentation and understanding of how shoppers differ in their behaviors. Our findings draw attention to the important role of the choice of carrying equipment in understanding in-store behavioral patterns. Our data show heterogeneity in shopping trips connected to type of carrying equipment, and based on the results, we find carrying equipment to be a suitable variable for segmenting shoppers. It is an objective and observable measure and also predictive in terms of occurring before the in-store behavior. Although carts and baskets have been around for many decades (Grandclément, 2009) and still today provide valuable customer service for shoppers, surprisingly few studies investigate their association with behavioral patterns in the store.

We find non-equipment use to be widespread across stores and retail formats and to represent a considerable proportion of shoppers. We contribute unique and important insight on how this segment of shoppers behave compared to those using either a basket or a cart. The findings indicate that non-equipment users on average walk at a faster pace, visit a smaller share of the store area, walk shorter distances, spend less time in the store, buy fewer items, and exhibit lower shopper efficiency than cart users (while basket users show behaviors that lie in between). Although we cannot conclude anything about causality, we show that carrying equipment can be used to capture the heterogeneity in these key behavioral metrics. Thus, by not distinguishing between different in-store carrying equipment, researchers examining shopping trips and in-store behaviors unintentionally neglect an important discriminator for differences in key behavioral metrics.

5.3. Limitations and suggestions for further studies

While conducting this study, we faced methodological issues related to shopping trips involving multiple shoppers (e.g. families, couples and groups) that led us to focus only on single-person shopping trips in the analysis of our data. A shopping trip with multiple shoppers introduces sources of potential bias that must be overcome. For instance, who

should be tracked? What if the group splits up one or more times during the trip and more than one member purchases items?

Another dilemma is how to profile the shopping trips using relevant shopper characteristics such as gender and age. In cases where shoppers shop together as a group, most likely more than one age group and gender are involved. Shopper characteristics can be rather ambiguous if used for trips involving multiple shoppers. We used visual inspection to determine age and gender. Therefore, please note that the data on these variables may be subject to some measurement error.

When the shopping trip is the unit of analysis, then the entry and the exit measures become important not only for between-study comparisons but also for the validity of the fundamental behavioral metrics: those based on time in particular. Shoppers may spend a lot of time both at the start and at the end of the shopping trip on tasks not associated with purchases (e.g., picking a basket/cart, queuing at the checkout, and item scanning). Measures for when to start and stop tracking should be established, and all studies examining in-store behavioral patterns should apply these. Our procedure was to stop tracking when the shopper started queuing, or in the absence of a queue, when the shopper placed the first item on the conveyor belt. One concern is that subsequent purchases (e.g., items displayed at the checkout) are not added to the number of purchases since they occur after the defined shopping trip.

In this paper, we introduce average walking speed, but measuring walking speed within each area would be an improvement as it could add further insight regarding shopping patterns. We also recognize that the behavioral metrics do not provide any insight as to shoppers' actual attention to stimuli along their in-store path. Store area coverage, travel distance and shopping duration are only indicative of opportunities to notice in-store stimuli, and average walking speed is only indicative of the shopper's search activity, visual field, and attentiveness to stimuli. It seems that there is a need for a more fine-tuned measure of attentional patterns based on, for instance, eye-tracking that can complement the other key behavioral metrics. Further research should therefore explore this opportunity.

5.4. Implications for retailers

Our data point to a high extent of non-equipment trips in grocery retailing and that in many stores, the shopping cart has passed to a more marginal role overall in terms of use on shopping trips. Since carrying equipment expands consumers' shopping capacity and is related to increased buying, physical retailers need to monitor, nurture and reward carrying equipment use. Observing consumers' choice of carrying equipment at the entrance should be an important retail metric, which can act as a benchmark for measures intended to increase the likelihood of shoppers selecting a piece of carrying equipment and for benchmarking against competitors. By deciding on which types of equipment to offer shoppers, in terms of the stock size for each alternative and their pick-up location in the store, retailers set the scene for their customers' choice of carrying equipment (including no equipment). Miscalculating the size of the need for a given type (resulting in periods of unavailability), or failure to offer shoppers the right types of equipment (small/large; plastic/metal) at the appropriate place (at the entrance/close to the entrance/inside the store), can presumably result in more non-equipment use. Optimizing the number of shoppers selecting a shopping cart should be the aim of most retail grocery stores. Retailers should focus on making it easy and appealing to select a cart and avoid any barriers to cart use, such as cart locks. This includes drawing attention to the benefits of or increasing the consumer value from using a cart. For instance, technology mounted on shopping carts (so called "smart carts") can offer consumers other types of benefits than the regular shopping cart (e.g., assistance in finding relevant products). Retailers could also attach discounts or reward points to cart use to motivate shoppers to select a cart for their shopping.

A high extent of non-equipment use also points to the need to offer

shoppers suitable carrying equipment at secondary locations in the store. Shoppers occasionally misjudge their need of carrying capacity at the start of their shopping trip. This is evident, for example, from situations where shoppers are trying to stretch the capacity of what their arms are capable of handling. Thus, placing equipment inside the store can lead shoppers to easily upgrade their choice of carrying equipment (without having to make the effort to retrace their steps to the entrance). This is customer service that may contribute to a more pleasant experience and improve sales.

We have shown that non-equipment trips are the least efficient among all shopping trips as measured in terms of purchases per meter travelled. For most retailers, the shopping trend is now moving dramatically in the direction of smaller, more frequent trips (Sorensen, 2016), many of which involve no carrying equipment. The paradox here is that non-equipment shoppers presumably are those who mostly seek a quick and efficient trip, but who in practice experience the least efficient trip among all shoppers. Our data suggest that non-equipment shoppers walk rather fast to the few products that initiated their visit. Nevertheless, they spend the longest time per item bought, and compared to other shoppers, their pace makes them less likely to be attentive to stimuli on their way to their in-store destination. To cater to a growing segment of non-equipment shoppers in a better way, retailers should consider using special shelves in close vicinity to the entry and checkout for products bought frequently by non-equipment shoppers.

Alternatively, retailers can attempt to establish a convenience store within their main store (store-in-store concept) stocking those items and categories that are most relevant for non-equipment users. Such store-in-store concepts have already started to appear in practice. Further, retailers can focus on initiatives that make the checkout more time efficient for non-equipment shoppers buying few items, such as self-checkout stations, express lanes, or no-checkout stores (such as Amazon Go). In addition, retailers can facilitate shortcuts in the store aimed particularly at reducing intra-store travel for non-equipment shoppers who know exactly what they want.

Our results suggest that carrying equipment is the best directly observable variable for segmenting shoppers as it explains a larger proportion of the variance in the in-store behavioral metrics than age and gender do. Segmenting on carrying equipment is objective and actionable in terms of product, place and promotion strategy. Further research could study this in terms of pricing and willingness to pay as well as in terms of in-store marketing communication. The problem with traditional retailing is that retailers show everything to everyone. By using, for instance, movement sensors and RFID tags in baskets and carts, targeted ads on in-store screens could be displayed (if movement, but no RFID is detected, then display ads targeted to non-equipment shoppers. If cart RFID is detected, then show ads to cart shoppers etc.). Thus, behavioral segmentation based on carrying equipment selection offers retailers the opportunity to segment customers.

Appendix 1. . Frequencies by choice of carrying equipment

Variable	No equipment	Basket	Cart	Total
Customer type				
Female	93	101	56	250
Male	136	112	24	272
Group/family	41	39	33	113
Total	270	252	113	635
Age[1]				
0–20	28	2	–	30
21–30	54	42	1	97
31–40	53	54	6	113
41–50	37	36	26	99
51–60	24	41	15	80
61–70	29	32	24	85
71 +	4	6	8	18
Total	229	213	80	522
Shopping period				
Weekday	185	172	78	435
Weekend	85	80	35	200
Total	270	252	113	635
Shopping time				
Off Peak	240	230	106	576
Peak	30	22	7	59
Total	270	252	113	635

[1] Age frequencies for female and male customers only.

Appendix 2. . Correlation matrix for the six key behavioral metrics (dependent variables)

	Shopping duration (min)	Walking speed (m/s)	Travel distance (m)	Area coverage (%)	Basket size	Shopper efficiency
Shopping duration (min)	1.0000					
Walking speed (m/s)	−0.6256	1.0000				
Travel distance (m)	0.8181	−0.3515	1.0000			
Area coverage (%)	0.7861	−0.3728	0.9423	1.0000		
Basket size	0.7895	−0.4230	0.7529	0.7276	1.0000	
Shopper efficiency	0.4596	−0.4203	0.2668	0.3163	0.7612	1.0000

The table shows that several behavioral metrics are highly correlated. This should be expected given the definition of the metrics. For instance, the longer distance a shopper travels in the store, the more time he or she spends in the store and thus on average, the longer the shopping duration. Despite being correlated, all behavioral metrics capture and explain different aspects of shopper behavior (see Sections 2.2–2.7). For instance, the high correlation between travel distance in meters and area coverage in percentage demonstrates that shoppers only to a small extent go back to previously visited store areas.

References

Atkins, K. G., & Kim, Y.-K. (2012). Smart shopping: Conceptualization and measurement. *International Journal of Retail & Distribution Management, 40*(5), 360–375. https://doi.org/10.1108/09590551211222349.

Beatty, S. E., & Smith, S. M. (1987). External search effort: An investigation across several product categories. *Journal of Consumer Research, 14,* 83–95.

Bell, D. R., Corsten, D., & Knox, G. (2011). From point of purchase to path to purchase: How preshopping factors drive unplanned buying. *Journal of Marketing, 75*(1), 31–45.

Bogomolova, S., Vorobyev, K., Page, B., & Bogomolov, T. (2016). Socio-demographic differences in supermarket shopper efficiency. *Australasian Marketing Journal, 24*(2), 108–115.

Cochoy, F. (2008). Calculation, qualculation, calqulation: Shopping cart arithmetic, equipped cognition and the clustered consumer. *Marketing Theory, 8*(1), 15–44.

Davies, G., & Bell, J. (1991). The grocery shopper — Is he different? *International Journal of Retail & Distribution Management, 19*(1), 25–29.

Davis, L., & Hodges, N. (2012). Consumer shopping value: An investigation of shopping trip value, in-store shopping value and retail format. *Journal of Retailing and Consumer Services, 19*(2), 229–239. https://doi.org/10.1016/j.jretconser.2012.01.004.

Gil, J., Tobari, E., Lemlij, M., Rose, A., & Penn, A. R. (2009). The differentiating behaviour of shoppers: Clustering of individual movement traces in a supermarket. In: D. Koch, L. Marcus & J. Steen (eds.). Proceedings of the 7th International Space Syntax Symposium. Royal Institute of Technology (KTH): Stockholm, Sweden.

Granbois, D. H. (1968). Improving the study of customer in-store behavior. *Journal of Marketing, 32*(4), 28–33.

Grandclément, C. (2009). Wheeling one's groceries around the store: The invention of the shopping cart, 1936–1953. In W. Belasco, & R. Horowitz (Eds.). *Food Chains: Provisioning from Farmyard to Shopping Cart* (pp. 414–448). University of Pennsylvania Press.

Helbing, D., Molnár, P., Farkas, I. J., & Bolay, K. (2001). Self-organizing pedestrian movement. *Environment and Planning B: Planning and Design, 28,* 361–383. https://doi.org/10.1068/b2697.

Hui, S. K., Fader, P. S., & Bradlow, E. T. (2009a). The traveling salesman goes shopping: The systematic deviations of grocery paths from TSPOptimality. *Marketing Science, 28*(3), 566–572.

Hui, S. K., Fader, P. S., & Bradlow, E. T. (2009b). Path data in marketing: An integrative framework and prospectus for model building. *Marketing Science, 28*(2), 320–335.

Hui, S. K., Bradlow, E. T., & Fader, P. S. (2009c). Testing behavioral hypotheses using an integrated model of grocery store shopping path and purchase behavior. *Journal of Consumer Research, 36*(3), 478–493.

Hui, S. K., Inman, J. J., Huang, Y., & Suher, J. (2013). The effect of in-store travel distance on unplanned Spending: Applications to mobile promotion strategies. *Journal of Marketing, 77*(2), 1–16.

Inman, J. J., & Nikolova, H. (2017). Shopper-facing retail technology: A retailer adoption decision framework incorporating shopper attitudes and privacy concerns. *Journal of Retailing, 93*(1), 7–28. https://doi.org/10.1016/j.jretai.2016.12.006.

Inman, J. J., Winer, R. S., & Ferraro, R. (2009). The interplay among category characteristics, customer characteristics, and customer activities on in-store decision making. *Journal of Marketing, 73,* 19–29.

Kollat, D. T., & Willett, R. P. (1967). Customer impulse purchasing behavior. *Journal of Marketing Research, 4*(1), 21–31. https://doi.org/10.1177/002224376700400102.

Larsen, N. M., & Sigurdsson, V. (2019). What affects shopper's choices of carrying devices in grocery retailing and what difference does it make? A literature review and conceptual model. International Review of Retail, Distribution & Consumer Research , 29(4), 376–408. Doi: https://doi.or/10.1080/09593969.2019.1581074.

Larsen, N. M., Sigurdsson, V., & Breivik, J. (2017). The use of observational technology to study in-store behavior: Consumer choice, video surveillance, and retail analytics.

The Behavior Analyst, 40(2), 343–371. https://doi.org/10.1007/s40614-017-0121-x.

Larsen, N. M., Sigurdsson, V., Breivik, J., Fagerstrøm, A., & Foxall, G. (2019). The Marketing Firm: Retailer and consumer contingencies. *Managerial and Decision Economics, 1–13.* https://doi.org/10.1002/mde.3053.

Larson, J. S., Bradlow, E. T., & Fader, P. S. (2005). An exploratory look at supermarket shopping paths. *International Journal of Research in Marketing, 22*(4), 395–414.

Liu, J., Gu, Y., & Kamijo, S. (2017). Customer behavior classification using surveillance camera for marketing. *Multimedia Tools and Applications, 76*(5), 6595–6622. https://doi.org/10.1007/s11042-016-3342-1.

Malhotra, N. K., & Birks, D. F. (2007). Marketing research: an applied approach. 3rd European edition. Harlow, England: FT Prentice Hall.

Nielsen (2014). Continuous innovation: The key to retail success. The Nielsen Company. Accessible from https://www.nielsen.com/ng/en/insights/reports/2014/continuous-innovation-the-key-to-retail-success.html (Accessed September 19, 2019).

Nielsen (2015). The future of grocery: e-commerce, digital technology and changing shopping preferences around the world. April 2015. Available at < http://www.nielsen.com/us/en/insights/reports/2015/the-future-of-grocery.html > (accessed June 10, 2017).

Peterson, H. (2015). What it's like inside Wal-Mart's new marketplace that's a threat to Whole Foods and Trader Joe's. Businessinsider.com, July 4. Available at < https://www.businessinsider.com/inside-walmarts-neighborhood-markets-2015-7?r=US&IR=T&IR=T > (Accessed August 16, 2018).

Phua, P., Page, B., & Bogomolova, S. (2015). Validating Bluetooth logging as metric for shopper behaviour studies. *Journal of Retailing and Consumer Services, 22,* 158–163. https://doi.org/10.1016/j.jretconser.2014.10.009.

Scamell-Katz, S. (2004). Understanding the shopper: The key to success. *Young Consumers, 5*(4), 53–55.

Scamell-Katz, S. (2012). *The art of shopping: How we shop and why we buy.* UK: LID Publishing.

Seiler, S., & Pinna, F. (2017). Estimating search benefits from path-tracking data: Measurement and determinants. *Marketing Science, 36*(4), 471–643.

Sorensen, H. (2009). The in-store "audience". *Journal of Advertising Research, 49*(2), 176–179. https://doi.org/10.2501/S0021849909090242.

Sorensen, H. (2016). Inside the mind of the shopper: The science of retailing. Second Edition. Old Tappan, New Jersey: Pearson Education.

Sorensen, H., Bogomolova, S., Anderson, K., Trinh, G., Sharp, A., Kennedy, R., & Wright, M. (2017). Fundamental patterns of in-store shopper behavior. *Journal of Retailing and Consumer Services, 37,* 182–194. https://doi.org/10.1016/j.jretconser.2017.02.003.

Statista (2018). Total number of Walmart stores in the United States from 2012 to 2018, by type. Available at < https://www.statista.com/statistics/269425/total-number-of-walmart-stores-in-the-united-states-by-type/ > (Accessed August 16, 2018).

Steiner, R. (2018). Co-op launches £160m expansion plan for 2018 (2 January, 2018). Available at < https://www.theguardian.com/business/2018/jan/02/co-op-launches-160m-expansion-plan-for-2018 > (Accessed 17 January, 2019).

Underhill, P. (1999). *Why we buy: The science of shopping.* New York, NY: Simon & Schuster.

Underhill, P. (2009). *Why we buy: The science of shopping—updated and revised for the Internet, the global consumer, and beyond.* New York, NY: Simon & Schuster.

Van den Bergh, B. V., Heuvinck, N., Schellekens, G. A., & Vermeir, I. (2016). Altering speed of locomotion. *Journal of Consumer Research, 43*(3), 407–428.

Van den Bergh, B. V., Schmitt, J., & Warlop, L. (2011). Embodied myopia. *Journal of Marketing Research, 48*(6), 1033–1044.

Wagner, U., Ebster, C., Eske, U., & Weitzl, W. (2014). The influence of shopping carts on customer behavior in grocery stores. *Marketing ZFP, 36*(3), 165–175.