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Fundamental patterns of in-store shopper behavior

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A R T I C L E I N F O

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A B S T R A C T

This research confirms empirical patterns about in-store behaviors based on a large number of shops and store visits, specifically 654,000 transactions in 40 supermarkets, hypermarkets, convenience and specialty stores in the USA, UK, China, and Australia. Integrating new data with past findings highlights that: (i) many shopping trips are short; (ii) shoppers typically only cover a small proportion of the store on any trip, and (iii) the heterogeneity of key behavioral measures (store coverage, number of items bought, and trip length) is generalizable across countries, most store formats, and store size. These patterns can help retailers and manufacturers benchmark and predict behavior and provide a base for further theoretical developments.

1. Introduction

The in-store behavior of shoppers has been studied for more than 60 years (e.g. see Applebaum, 1951; Frisbie, 1980; Kollat and Willett, 1967; Stern, 1962). However, more systematic documentation of the underlying patterns of shopper behavior remains necessary. The retail sector has increased in complexity, where retailers now operate stores in multiple retail formats (i.e. supermarkets, supercenters, convenience, online) across a range of countries. Similarly, manufacturers increasingly sell their products across a range of retail formats and countries (Deloitte, 2013).

While models to describe consumers switching between retail outlets (Keng et al., 1998), regularity of shopping trips (Kim and Park, 1997), and shopper purchases (Kamakura, 2012) have been identified, models to describe shopper behavior inside retail outlets are scarce and largely based on laboratory rather than field experiments (Hui et al., 2009c). Prior research has established that consumers vary in their motivations for shopping (e.g. Tauber, 1972), shopping styles (e.g. Inman et al., 2009; Kollat and Willett, 1967), in-store behaviors (e.g. Kim and Park, 1997; MacKay, 1973) and frequency of shopping trips. However, a better understanding of the heterogeneity of shopper behavior inside retail outlets is needed and is possible.

We focus on three related metrics relevant to the management and design of retail outlets and to the implementation and evaluation of shopper marketing programs: the proportion of the store visited on a shopping trip, the number of items purchased per shopping trip (basket size), and the amount of time spent in the store. The proportion of store area visited is particularly under-researched, despite its relevance to retailers, manufacturers, and researchers.

We utilize data from 42 retail outlets to identify generalizable patterns of shopper behavior. Consistent with an empirical generalizations approach, the data was purposefully selected to provide both close replications (i.e. supermarkets in different US cities) and differentiated replications (a hypermarket in China, specialist wine stores in Australia) to test the generalizability of the findings (as recommended by Lindsay and Ehrenberg, 1993).

2. Key shopper metrics and current knowledge

To build a comprehensive description of in-store behavior to advance the science of shopping (Underhill, 1999), a multi-measure approach providing insight into different aspects of in-store behavior is useful. For example, the proportion of a store covered may be determined by how much time the shopper has available to spend in the store or the items the shopper intends to purchase. Alternatively, the items needed may dictate how much of the store the shopper covers, which may, in turn, influence the time taken to complete a shopping trip. There will be variation across individuals and across shops. Regardless of the direction of these relationships, all measures—trip length, store coverage, and basket size—yield valuable insights into how shoppers behave. While clearly the measures are correlated and there is important work (e.g. in-store experiments) required to under-

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stand how they influence each other across conditions, documenting "norms" and typical patterns in each is an important step to advance our knowledge out how people shop and to develop evidenced based benchmarks for evaluating in store activations.

Of all the aspects of shopper behavior in-store, we intentionally focus on some of the most fundamental patterns to ensure that the knowledge we develop will be understood and adopted by industry. Starting by describing a number of measures is also a critical step in building an empirically based theory of in-store shopper behavior. The scope of this work is brick-and-mortar retail environments. We acknowledge that there is an opportunity in the data-rich online shopping environment to build further generalizations (for a relevant discussion see Moe and Fader (2001)).

The present research builds on scattered prior studies, looking for fundamental patterns in the heterogeneity of in-store shopper behavior. It does this through examining store coverage, shopping trip length, and basket size across a wide range of primary data sources and through incorporating industry based, ad hoc prior studies. Through this, we provide a more comprehensive explanation of the observed patterns in shopper behavior and establish a solid empirical basis from which differences in varying contexts can be identified.

2.1. Store coverage

The first measure, how much of the store a shopper covers on a single trip, plays a critical role in the effectiveness of in-store marketing activities. To be influenced by in-store stimuli (e.g., at-shelf promotions, product arrangement, or in-store communications), shoppers must first visit specific areas of the store. Exposure is also important for generating unplanned (impulse) purchases (Granbois, 1968; Hansen and Ottar Olsen, 2007; Hui et al., 2013a; Knox et al., 2011; Kollat and Willett, 1967; Stern, 1962). In addition, assumptions about store coverage affect store design. For example, some retailers attempt to minimize walking distance, believing that shoppers find it inconvenient (e.g. Tauber, 1972).

Historically, marketers have assumed that shoppers methodically work their way up and down each store aisle (see Larson et al. (2005) for further discussion). Even shoppers themselves believe they behave this way: 25% of shoppers claimed to visit the entire store on their shopping trips (Scamell-Katz, 2012). However, in-store observations revealed a different reality: of the 25% who claimed to visit the whole store, camera footage showed that less than 2% covered more than half of the store (Scamell-Katz, 2012). Trolley tracking studies also support an extremely low occurrence of shopping trips that cover every aisle (Silberer et al., 2007; Sorensen, 2009).

Prior studies and logic indicate that the proportion of store area visited is affected by store size. For example, Sorensen (2011b) reported that, on average, shoppers visited just 11% of a 9000 m^2 US supercenter and 25% of a 3700 m^2 US supermarket (Hui et al., 2013a). Similarly, Hui et al. (2009a) reported that shoppers of a large US supermarket visited, on average, 26% of the store whilst shoppers of a medium-sized US supermarket visited 37%. However, prior studies have not discussed the distribution that coverage statistics follow, and have not systematically documented the patterns in stores of different sizes, to determine if a consistent distribution is evident across different retail formats, store sizes or countries. Understanding the distribution of store coverage by shoppers will enable retailers and managers to forecast the intensity of shopper traffic and to benchmark the performance of stores.

2.2. Shopping trip length

The amount of time spent in a store (trip length or duration) may moderate how much of a retail outlet a shopper covers. The amount of time in-store also affects how shoppers navigate the outlet (Larson et al., 2005) and make purchase decisions (Dhar and Nowlis, 1999; Park et al., 1989).

Shopping trips vary in length, depending on the shopping mission (Walters and Jamil, 2003), the day of the week (LLT 1995 as cited in Kahn and Schmittlein, 1989; Tanskanen et al., 2002), and the retail environment (Sorensen, 2009). For example, trips vary across retail formats, with trips to mass merchandise stores typically being longer than to grocery stores (Sorensen, 2009, 2011b). Sorensen (2010) also reports that shopping trips are typically longer in retail outlets with a single dominant pathway (e.g. Ikea or Stew Leonards supermarkets), compared to outlets where many pathways are possible. Store layout can also affect the distribution of trip length data (Sorensen, 2010).

Prior research has indicated that quick trips are most common (e.g. of all shops that occur in a store most are short) but that there is substantial variation in trip length (e.g. sometimes shoppers have long shops) (Kahn and Schmittlein, 1989; Sorensen, 2009). Systematic efforts to describe the characteristics of the variation in trip length have not been made despite its' relevance to retailers and manufacturers. Variability presents a problem for retailers as it suggests that shoppers have different needs and meeting those needs with a single approach or layout may be difficult.

Prior studies suggest that shopping trips are longer, on average, in some countries that in others; hypermarket trips in Asia have been found to be longer on average than in the US (i.e. Hui et al., 2009a; Scamell-Katz, 2012; Sorensen, 2010). Modeling the distribution and testing its generalizability across factors that have been shown to affect measures of central tendency is an important step towards developing knowledge that is broadly applicable.

2.3. Basket size or the number of items purchased

Basket size is both a driver of in-store behavior and a consequence of the path a shopper takes (Granbois, 1968; Knox et al., 2011; Kollat and Willett, 1967; Stern, 1962). The number of items purchased is a key measure for retailers and manufacturers when tracking the effectiveness of shopper marketing programs.

Basket size is expected to correlate with the amount of money spent on a grocery trip and the frequency of grocery trips (Desai and Talukdar, 2003). Basket size is also influenced by the type of shopping trip (whether a 'major/regular' or a 'fill-in/quick' trip) (Kahn and Schmittlein, 1989; Kollat and Willett, 1967); the planned or unplanned nature of the purchases (Granbois, 1968); the use of a shopping list (Thomas and Garland, 1993); and available shopping aids (basket, trolley, etc.) (Underhill, 1999).

Basket size can vary across different retail formats. For example, consumers may go to a neighborhood store for quick fill-in trips and to a larger store for regular weekly shopping trips (Kahn and Schmittlein, 1989; Leszczyc et al., 2000). Consistent with this observation, Sorensen (2009) found that, in supermarkets, 50% of baskets held five or fewer items but, in convenience stores, 50% of baskets had three or fewer items.

Cross-country variations in basket size have also been noted. For example, in the US, where cars are large and houses typically have ample storage space, large monthly shopping trips are common; however, in Vietnam, where bicycles and motorbikes are the primary modes of transportation, daily shopping is the norm (Scamell-Katz, 2012).

Thus, empirical examination of the distribution of shopping trips across stores of different sizes, formats and countries can be used to test the applicability of prior claims and to test whether it is possible to establish a generalizable pattern about the distribution of basket sizes at a store level.

2.4. Heterogeneity of shopping trips

Industry and academic researchers (e.g. Larson et al., 2005; Sorensen, 2008, 2009; Underhill, 1999) have observed substantial heterogeneity in the behaviors of shoppers – even within an individual store. Understanding the heterogeneity of shopper behavior will aid managerial efforts in meeting shoppers' needs.

The traditional approach to understanding heterogeneity has been to segment shoppers into clusters (e.g. Kahn and Schmittlein, 1989; Larson et al., 2005; Sorensen, 2009) or compare shoppers with different demographic characteristics (e.g. men versus women) or behaviors (e.g., browsers versus buyers) across a single measure. These approaches are premised on discrete groups existing rather than a continuum of behaviors. Given that individual shoppers have been shown to display different behaviors on different shopping trips (Sorensen, 2009), an approach that uses individual ***trips*** (not ***shoppers***) and examines the distribution of behaviors is needed to establish the variance in shopping trips.

Some initial attempts have been made. The number of 'fill-in' shopping trips taken by households was modeled using the negative binomial distribution; a distribution which is unimodal with a strong positive skew (Frisbie, 1980). The occurrence of quick and regular shopping trips was described as a Poisson process (Kahn and Schmittlein, 1989); the frequency of individuals' shopping trips was modeled by a gamma distribution and their regularity by a combined exponential and Erlang-2 model (Kim and Park, 1997). Kim and Park (1997) also noted that the frequency of individuals' shopping trips was unimodal and negatively skewed. In addition, basket size distributions have been found to be highly polarized, with a skew to smaller baskets at the store level (Russell and Petersen, 2000). However, the generalizability of these patterns across countries and retail formats has not been investigated. This is important if we are to identify boundary conditions with confidence.

3. Research approach

3.1. Empirical generalizations

To document patterns in shopper behavior, we follow the empirical generalizations approach espoused by Ehrenberg, (1995, 2000) and Bass and Wind (1995). This approach has been effective in guiding development of new knowledge in consumer behavior, including consumer switching between retail outlets and rates of purchase of different product categories (Uncles and Ehrenberg, 1990; Uncles and Kwok, 2009) purchasing of retailers' own brands (Dawes and Nenycz-Thiel, 2011; Uncles and Ellis, 1989), and the tendency of competing retailers to attract demographically and psychographically similar shoppers (Kennedy and Ehrenberg, 2001). In addition, using this approach has helped establish empirical benchmarks for measuring and interpreting behaviors in new areas, such as social media (Nelson-Field et al., 2012) and new markets (Kennedy and McColl, 2012; Uncles and Kwok, 2013).

The approach is underpinned by many sets of data (MSoD) covering different conditions to test whether an identified pattern or model is generalizable (Ehrenberg, 1995). The purposeful selection of data is recommended to provide both close and differentiated replications for checking the initial results and searching for possible boundary conditions (Lindsay and Ehrenberg, 1993).

We systematically describe MSoD covering different conditions to establish patterns and models that are generalizable (Ehrenberg, 1995; Lindsay and Ehrenberg, 1993). Data from progressively different contexts was analyzed (e.g. from US hypermarkets in different cities through to Chinese hypermarkets, and specialty Australia wine stores) and the patterns in each data set examined to establish both consistencies and boundary conditions. The data sets are detailed in Appendix A. Due to differences in the structure of the data across retail contexts it is not possible to model all three key variables at once. Instead, we explore the generalizability of the parameters for each shopper metric separately.

3.2. Data collection

The data were collected through naturalistic observation of real shopping trips by using both mechanical tracking of shopping carts (i.e., electronic carts with radio frequency identification [RFID] tags) and manual observation by researchers in store. The value of observing shoppers in situ has been discussed by many researchers (e.g. Bloch et al., 1994; Granbois, 1968; Shankar et al., 2011). Natural observations of shoppers in-store have superior validity to experiments in laboratory environments or shoppers' self-reports (East and Uncles, 2008; Lee and Collins, 1999; Rust, 1993; Scamell-Katz, 2012; Schwarz, 1999). Because shoppers are often not conscious of habitual behaviors, self-reports may be little more than a post-hoc rationalization of what shoppers believe they do in store (Martin and Morich, 2011; Underhill, 1999). Furthermore, shoppers have a tendency to forget routine behaviors (East et al., 2008; Sudman and Bradburn, 1973). In contrast to survey data, observational data provide a reliable foundation for establishing empirical generalizations about the nature of shopper behavior.

Data from an impressive range of observational sources was utilized. Specific details about the primary data collection are provided in Appendix B.

4. Key variables

4.1. Dependent variables

4.1.1. Store coverage

Proportion of area visited or passed by at least once on a shopping trip. In supermarkets and hypermarkets, RFID tracking devices on shopping carts and baskets tracked the proportion of trips passed within 1.8 m of each product display or area. Shoppers passing one side of an aisle were recorded as having passed the area directly opposite due to the narrowness of supermarket aisles and the potential for shoppers to both see and shop products located on both sides of the aisle.

RFID data is affected by two limitations. First, trips that do not involve a cart or basket are not tracked; so shopping trips covering a small number of areas are likely to be under-represented. Thus, measures of central tendency may be somewhat inflated and measures of variance somewhat reduced. Second, shoppers were not tracked as they left their cart or basket to retrieve items from other areas of the store, possibly reducing measures of central tendency.

To address these limitations, a representative sample of RFID trips was selected to match retailer transaction logs that provide a complete census of all purchases. Shoppers' carts/baskets were also screened for items located in store areas where their carts/baskets did not visit, and records were adjusted. Although such post-hoc adjustments are not ideal, until individual shoppers can be tracked easily and reliably with technologies like RFID belts as with Hui et al. (2013b) or their mobile phones, data from shopping carts and baskets provide a reasonable proxy for shopper behavior. In the smaller specialty Australian stores, researchers systematically manually recorded the areas of the store visited by a sample of shoppers. Areas visited multiple times were counted once.

4.1.2. Trip length

Duration in minutes/seconds from entering the store until reaching the checkout or exiting the store. Where data were derived from RFID tracking, trip length was measured from entry until a transaction was commenced at checkout. Time spent at a checkout prior to a transaction was counted towards the trip duration. (Waiting time results: mean 1 min 11 s, median 48 s) In Australian supermarkets, the total time from store entry to exit was measured by a Bluetooth tracking device near the entrance of the store that recorded shoppers as they passed within 10 m. Where trip length was monitored electronically, trips of less than 2 min were removed to reduce the possibility of including casual passers-by or carts/baskets used by staff. This is consistent with previous research (Hui et al., 2009c; Larson et al., 2005; Sorensen, 2003a; 2003b). In Australian small format stores, the time from entry until exit was captured manually using stopwatches.

4.1.3. Basket size

Number of different products purchased in a single transaction. This data was mainly captured through retailer transaction records or by manual examination and recording from consumer receipts during exit interviews (for Australian specialty stores). Multiple purchases of the same product were recorded as one product (between 1% and 13% of supermarket purchases). This is consistent with other research (Kollat and Willett, 1967; Sorensen, 2009; Thomas and Garland, 1993) and is appropriate here because the proportion of the store covered is unlikely to be affected by multiple purchases of the same item.

While these three measures are related, aggregate level correlation results indicate they are measuring different aspects of shopper behavior: Time-Coverage r=0.26, Items-Coverage r=0.13 and Time-Items r=0.86. Combining the measures to create a composite general index of in-store behavior maybe a useful as one benchmark for retail management. However, here each is examined each in isolation to provide readers with concrete, transparent results which are critical for benchmark setting and incorporation into future research in this space.

4.2. Independent variables

Three independent variables that influence shopping trip length, basket size, and in-store behavior were identified from prior research. The variables we adopted relate to characteristics of the retail outlets.

1. *Country:* USA (n=15), UK (n=1), China (n=1), Australia (n=25 for Stage 1, n=22 for Stages 2 and 3 of analysis)
2. *Retail format:* Hypermarkets (n=3), supermarkets (n=19 for Stage 1, n=12 for Stages 2 and 3), drug/convenience (n=9 for Stage 1, n=7 for Stages 2 and 3), specialty liquor (n=12). Definitions of store formats vary across countries (Peterson and Balasubramanian, 2002; Sharp, 2013), so we detail our categorizations in Appendix C.
3. *Outlet size:* Retail outlets studied ranged in size from 200 m^2 (specialty and convenience stores) to over 15,000 m^2 (hypermarkets). Less than 200 m^2 (n=10), 200–299 m^2 (n=11), 1700–3699 m^2 (n=8), 3700–5500 m^2 (n=8), more than 5500 m^2 of retail space accessible by shoppers (n=3).

5. Analysis approach

Our analysis occurred in three stages:

1. Exploratory analysis to describe the descriptive statistics and distributions of the primary data sets and compare them to previously reported findings;
2. Modeling the distribution of the primary data sources to describe the heterogeneity of shopping trips in terms of store coverage, trip length, and basket size;
3. Testing generalizability of the model parameters across retail formats, countries, and outlets of varying size.

5.1. Stage 1: calculating and comparing descriptive statistics

The mean, median, and standard deviation of the dependent variables are shown in Table 1 through Table 3.

Table 3. Averages weighted by the sample number of stores are included to demonstrate the similarity of results across countries, store formats, and sizes. This display of data is consistent with our objective of identifying empirical patterns that hold across stores.

Consistent with the empirical generalization approach, 11 prior studies that reported store coverage, trip length, or basket size metrics are integrated into these tables as secondary data. Some reported on similar regions and store formats, and a few used similar data sources (e.g., Bradlow and Hui, 2012; Hui et al., 2009a, 2009b; Larson et al., 2005; Sorensen, 2003b, 2009). They cover at least four additional markets including New Zealand, Croatia, and other unspecified European and Asian countries. Our interest is in studies that report direct observation of shoppers, RFID tracking of shopping carts/baskets, or trace evidence collected in-store (i.e., shoppers' receipts, point-of-sale transaction records).

5.2. Stage 2: modeling the distribution of the key shopper metrics

We used a logit-normal distribution to model the proportion of store area covered, as this distribution transforms the naturally occurring normal distribution to proportions.

The probability density function of the logit-normal distribution is as follows:

$$f(\lambda;\mu,\sigma)=\frac{1}{\sigma\sqrt{2\pi}}\exp\left\{-\frac{(\text{logit}(\lambda)-\mu)^2}{2\sigma^2}\right\}\frac{1}{\lambda(1-\lambda)} \tag{1}$$

where μ is the mean and σ is the standard deviation of the normal distribution Y where $Y=\text{logit}(\lambda)$.

We used a lognormal distribution to model the time spent in store, as this distribution had strong theoretical appeal (Laurent, 2013; Lawrence, 1980; Trinh et al., 2014). If the underlying heterogeneity of shopping trips is affected by many independent and unobserved factors, such as differences in shopping trip needs, shoppers’ responses to in-store marketing, and store layout, together with physical and temporal constraints, the multiplicative effect of these factors may converge to form a lognormal distribution based on the central limit theorem (Aitchison and Brown, 1969; Cassie, 1962; Johnson et al., 1994; Winkelmann, 2008).

The probability density function of the lognormal distribution is as follows:

$$f(\lambda;\mu,\sigma)=\frac{1}{\lambda\sigma\sqrt{2\pi}}\exp\left\{-\frac{(\log\lambda-\mu)^2}{2\sigma^2}\right\} \tag{2}$$

where μ is the mean and σ is the standard deviation of the normal distribution Y where $Y=\log(\lambda)$.

We used mixed Poisson lognormal distribution to model the third metric – the number of products purchased on a shopping trip (basket size). The continuous lognormal distribution was transformed into a discrete distribution by combining it with the Poisson distribution using the following assumptions:

(a) Items purchased x of a given consumer follow a Poisson distribution with the mean rate of purchasing λ

$$f(x)_{poisson}=\frac{\exp(-\lambda)\lambda^x}{x!} \tag{3}$$

(b) The mean rates of purchasing λ of different consumers differ, and they are distributed lognormally as in (2)

By combining (3) and (2), the probability density function of x items purchased results in a mixed Poisson lognormal (PLN) distribution is as follows:

$$\begin{aligned}f(x)_{PLN}&=\int_0^\infty f(x)_{poisson}f(\lambda;\mu,\sigma)d\lambda\\&=\frac{1}{x!\,\sigma\sqrt{2\pi}}\int_0^\infty\lambda^{x-1}\exp(-\lambda)\exp\left\{\frac{(\log\lambda-\mu)^2}{2\sigma^2}\right\}d\lambda\end{aligned} \tag{4}$$

Table 1
Descriptive findings: proportion of store areas covered in a shopping trip.

Context	Store size	Study	Sample stores	Sample trips	Method	Median	Mean	St. Dev. Mean
US	9 000 m^2	Sorensen (2011a, 2011b)	1	~3000	RFID	–	11%	–
US	15,000 m^2	Current study	**2**	5531	RFID	**6%**	**12%**	**11%**
China	19,000 m^2	Current study	**1**	20,231	RFID	–	**15%**	–
US	9000 m^2	Scamell-Katz (2012)	1	NA	In-store video	–	20%	–
Hypermarkets			**5**	**28,762**		**6%**	**14%**	**11%**
US	> 5500 m^2	Hui et al. (2009c)	1	1 051	RFID	–	26%	–
UK	3800 m^2	Current study	**1**	18,466	RFID	**20%**	**21%**	**8%**
US	> 3700 m^2	Current study	**6**	17,288	RFID	**23%**	**25%**	**12%**
US	3700 m^2	Sorensen (2003a, 2003b)	1	~3 000	RFID	–	25%	–
US	~3700 m^2	Hui et al. (2013a, 2013b)	1	275	RFID-S		37%	
US	< 3700 m^2	Current study	**5**	14,444	RFID	**33%**	**36%**	**15%**
US	1900 m^2	Sorensen (2011a, 2011b)	1	~3 000	RFID	–	33%	–
Supermarkets			**16**			**27%**	**30%**	**13%**
Au drug	300 m^2	Current study	**9**	1 300	Res obs	**23%**	**26%**	**13%**
Au spec'y liquor	200 m^2	Current study	**12**	3 110	Res obs	**11%**	**16%**	**11%**
Small format stores			**21**	**4 410**		**16%**	**21%**	**12%**
Total/Weighted Av.			**42**	**80,370**		**20%**	**23%**	**12%**

5.3. Stage 3: estimating heterogeneity parameters and testing their generalizability

For both trip length and proportion of store area covered, the maximum likelihood estimation (MLE) was used to obtain the parameters of the lognormal and logit-normal models for the 39 retail outlets for which data were available.

For the number of products purchased, parameters were estimated using the simulated MLE method proposed by Train (2009) because the probability of the PLN model does not have a closed form solution. The parameters of the PLN model were estimated through draws from a density, calculating the PLN model probability for each draw and averaging the results. For drawing from densities, Halton draws (Halton, 1960) were used because they provide better coverage than random draws and reduce the amount of error in the simulated log-likelihood function (Bhat, 2001; Hensher, 2001; Train, 2009). As the zero items purchased were not observed, we used the zero-truncated PLN model.

In all three models, the parameter μ is the log of the geometric mean and the parameter σ can be interpreted as the underlying heterogeneity of shoppers. Consequently, we are able to compare heterogeneities across different stores within each metric without the results being dominated by differences in the means (Good and Pirog-Good, 1989).

To test whether the underlying heterogeneity of shopping trips is generalizable across different retail formats, countries, and stores sizes, we tested for the effect of these variables on the parameter σ using three one-way MANOVAs. Retail format, country, and store size were incorporated as independent variables and trip length, store coverage, and basket size as dependent variables. Two-way MANOVAs were used to test for interaction effects between store size and country and store size and retail format.

6. Descriptive results and comparisons to prior findings

6.1. Store coverage

Across the 42 retail outlets and 80,000 odd shopping trips for which coverage data were available, the mean average proportion of store areas visited on a trip was 23%, indicating that the average shopping trip covered less than a quarter of the retail outlet. Descriptive statistics are shown in bold in Table 1 and show consistency across both the primary data and prior findings. This suggests that the new data are typical and can be used for developing generalizations about shopper behavior. Aggregate results split by each country and store type are also shown in Table 1. Averages are weighted by the sample number of stores to provide clear benchmarks for comparison. Results for individual retail outlets are detailed in Appendix C.

Consistent with prior industry findings (Sorensen, 2011b), shopping trips in larger retail outlets tend to cover a smaller proportion of the store (i.e., 14% for hypermarkets) while trips in smaller stores tend to cover a larger proportion of the store (i.e., 30% for supermarkets). Although small liquor stores in Australia deviate from this pattern (the proportion of store areas covered by the average shopper was just 16%), there is no reason to anticipate that the underlying heterogeneity in shopping trips would be different.

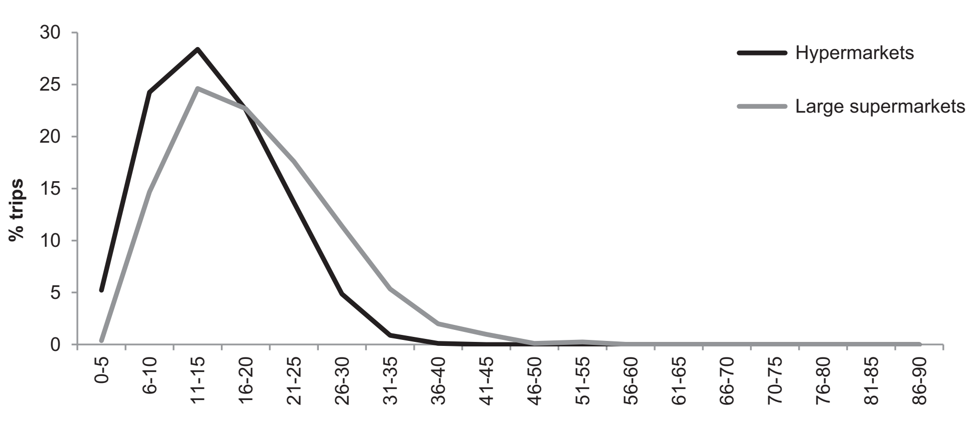

Fig. 1. Proportion of store areas covered in a single shopping trip.

Table 2
Descriptive findings: shopping time (minutes).

Context	Reference	Sample Stores	Sample Shoppers	Method	Median Mins	Mean Mins	St. Dev. Mins
Croatia	Anic and Radas (2006)	1	300	Interview at entrance	–	42	–
US	Sorensen (2010)	2	~4000	RFID	–	37	–
US	Current study	**2**	29,645	RFID	**32**	**37**	**22**
US	Hui et al. (2009a, 2009b, 2009c)	1	13,486	RFID	–	44	–
Asia	Scamell-Katz (2012)	1	NA	NA	–	50	–
China	Current study	1	20,231	RFID	**43**	**47**	**21**
Hypermarkets		**7**	**67,662**		**36**	**41**	**22**
US	Sorensen (2010)	1	~2000	RFID	10	18	15
US	Larson et al. (2005)	1	27,000	RFID	13	16	–
US	Current study	**11**	31,732	RFID	**18**	**20**	**13**
UK	Scamell-Katz (2012)	1	400	In-store video	–	27	–
Europe	Silberer et al. (2007)	1	80	Res obs	12	–	–
Europe	Bell et al. (2011)	**23**	441	Self-report	–	18	11
Nth Europe	Scamell-Katz (2012)	1	~2000	RFID	–	29	–
UK	Current study	1	18,466	RFID	**26**	**29**	**15**
Australia	Current study	**5**	10,525	BT	**18**	**25**	**22**
NZ	Thomas and Garland (1993)	4	232	Res obs	–	30	–
Supermarkets		**49**	**65,476**		**17**	**25**	**15**
US drug	Scamell-Katz (2012)	1	~1000	In-store video	–	5	–
Au drug	Current study	**9**	1225	Res obs	**4**	**6**	**5**
Au liquor	Current study	**12**	3110	Res obs	**2**	**4**	**3**
Small format stores		**23**	**5335**		**3**	**5**	**4**
Total/Weighted Av.		**78**	**135,473**		**12**	**19**	**10**

Although prior industry studies (Scamell-Katz, 2012; Sorensen, 2003b, 2011b) report simple averages, as Fig. 1 shows, store coverage results do not follow a normal distribution. This indicates the need to document the distribution of shopper behavior measures to determine the appropriate measures of variance and central tendency.

6.2. Trip length

Consistent with prior findings, the descriptive metrics for trip length vary across retail formats and, to a lesser degree, across countries (see Table 2). For example, trips to hypermarkets are longer in Asia than in the US, consistent with prior findings (i.e. Hui et al., 2009a; Scamell-Katz, 2012; Sorensen, 2010). This may be a consequence of cross-country differences, in-store crowding or queue length, or the novelty (and unfamiliarity) of the retail format in China. Trips to supermarkets in the US are also slightly shorter on average than in the UK and Australia.

While shopping trips in drug and specialty liquor outlets were typically short (median 3 min, mean 5 min), shopping trips in supermarket were longer (median 17 min, mean 25 min). However, there was a consistent pattern evident across all data, including prior studies: retail outlets skew towards short trips.

The descriptive results shown in Table 2 are for retail outlets with rows of aisles in a grid-like pattern and no dominant pathway.

Because many prior studies did not report variance, we cannot determine whether the heterogeneity of the current data sets is consistent across all situations. However, given the similarity of the mean and median results in Table 2, together with the similarity of methods, we have no reason to suspect dissimilarity in variance. The consistency of the results with prior findings again indicates that the data sources provide an adequate basis for developing generalizations about shopper behavior.

6.3. Basket size

Across the 53 retail outlets and 662,000 odd shopping trips shown in Table 3, the mean number of products purchased was nine and median was three (results weighted by number of stores). In all retail outlets, including those reported in prior studies, a consistent pattern is again evident: during most shopping trips, consumers purchased a relatively small number of items (i.e., fewer than 10 products).

Charts of basket data in Fig. 2 demonstrate the prevalence of small shopping trips in supermarkets and hypermarkets globally. Indeed, the most common basket size (mode) in 17 of the 18 outlets tracked was one, an observation previously reported by Sorensen (2009). Fig. 2 also shows the similarity of the distribution across a range of retail outlets. The data in Fig. 2 and subsequent figures are truncated, but shops of up to 120 products occurred at some retail outlets.

7. Modeling results

Fig. 3 shows an example of the fit achieved by the lognormal, logit-normal and Poisson lognormal models across the three measures by charting the observed data and the theoretical distributions. The data in Fig. 3 is truncated for illustrative purposes. The same fitting procedure was conducted on all the available stores, and the fit parameters were examined (Table 4).

Table 4 shows the parameters of the models for each store (σ and μ) and Theil's U between the observed and theoretical values for each variable. Theil's U ranges from 0 to 1 (Fader and Hardie, 2002; Wu and Chen, 2000). Scores approaching 0 indicate a good fit to the model. Across the 39 retail outlets modeled, the values of the Theil's U coefficient are typically small, ranging from 0.04 to 0.24 for time in store, 0.00–0.12 for proportion of store area covered, and 0.02–0.20 for the number of products purchased. These results demonstrate the good fit achieved by the lognormal, logit-normal and Poisson lognormal models across the range of retail formats, brands, and countries investigated.

7.1. Generalizability of shopping trip heterogeneity

The effect of country, store size, and retail format on the heterogeneity of store coverage, basket size, and trip length is non-significant. The one-way MANOVAs showed non-significant main effects for country, store size, and retail format (country: Wilks' Lambda=0.880, $F(3, 17)=0.773$, $p=0.525$; store size: Wilks' Lambda=0.756, $F(6, 32)=0.803$, $p=0.575$; retail format: Wilks' Lambda=0.450, $F(9, 36.657)=1.583$, $p=0.157$). The two-way MANOVAs showed a non-significant effect for the interaction of store size and country (Wilks' Lambda=0.434, $F(6, 26)=2.241$, $p=0.071$) and a non-significant effect for the interaction of store size and retail format (Wilks' Lambda=0.685, $F(6, 22)=0.763$, $p=0.607$). This confirms that the

Table 3
Descriptive findings – basket size (number of different SKUs).

Context	Reference	Sample Stores	Sample Shopp'	Method	Median Products	Mean Products	St. Dev. Products
US	Current study	**2**	29,645	Transaction records	**5**	**8**	**9**
China	Current study	**1**	377,658	TR	**5**	**7**	**7**
Hypermarkets		**3**	**407,303**		**5**	**8**	**8**
US	Kollat and Willet (1967)	8	596	Interviews & dockets	–	13	–
US	Current study	**11**	31,732	TR	**4**	**7**	**8**
US	Sorensen (2009)	1	~2000	TR	5	12	11
UK	Current study	**1**	18,466	TR	**9**	**15**	**15**
Australia	Current study	**3**	195,283	TR	**6**	**12**	**15**
UK	Scamell-Katz (2012)	1	400	In-store video	–	26*	–
NZ	Thomas and Garland (1993)	4	279	Interviews & dockets	–	39*	–
Supermarkets		**29**	**248,756**		**4**	**15**	**8**
US drug	Sorensen (2009)	1	~2000	TR	3	–	–
Au drug	Current study	**9**	1 225	Res obs	**1***	**2***	**1***
Au specialty	Current study	**12**	3 110	Interviews & dockets	**1***	**2***	**1***
Small format		**22**	**6335**		**1**	**1**	**2**
Total/Weighted Av.		**53**	**662,694**	* items purchased	**3**	**9**	**5**

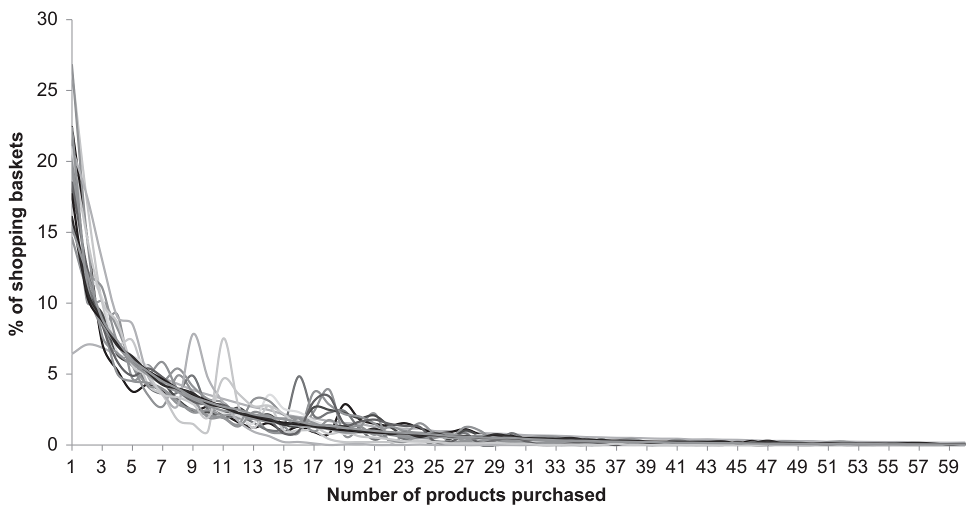

Fig. 2. Distribution of basket sizes in US, UK, Chinese, and Australian supermarkets and hypermarkets (n=18).

pattern of heterogeneity of basket size, trip length, and store coverage data are similar across different retail formats, store sizes and countries.

8. Conclusions and implications

In summary, we confirmed in large data and statistically described the distribution of three key shopper behavior measures. Our findings indicate that generalizable patterns exist across the three metrics, describing the heterogeneity of shopping trips. Across varied data points, we demonstrated store coverage, trip length, and basket size each show consistent patterns. The findings validate that shoppers on small trips, of which there are many/most, typically cover a small proportion of the store, shop quickly, and purchase just a few items. That retail outlets have many shoppers making small trips is consistent with patterns identified in brand buying: brands typically have a few heavy buyers and large numbers of light buyers (Ehrenberg, 2000; Sharp, 2010). Such knowledge has important implications for growth.

This research also demonstrates that it is possible to bring together a large amount of data from disparate sources (34 retail outlets from secondary sources and 42 retail outlets from primary sources) to identify patterns and develop benchmarks.

Understanding the patterns of shopper behavior that occur consistently across retail outlets, formats, and countries can help retailers and marketing managers in planning, predicting, and influencing shopper experiences. Furthermore, identifying such generalizability as well as boundary conditions lies at the cornerstone of scientific knowledge development (McCabe and Stern, 2009).

8.1. Implications

Generalizations about how shoppers behave in a store provide behavioral norms for marketers, retailers, and researchers. Just as architects should work within the laws of physics, marketers and retailers should tailor their interventions to work ***with*** rather than ***against*** these clear behavioral patterns (for further discussion on this see Kennedy and McColl, 2012). Given the intensity of competition in the retail sector (Knox and Denison, 2000; Leszczyc et al., 2000), retailers and manufacturers who understand the fundamental patterns of shopper behavior and adapt their practices will have a competitive edge (Sorensen, 2011a).

8.2. Implications for retailers

The ability to predict the heterogeneity of shopping trips in retail outlets allows for better planning and better servicing of customers involved in different types of shopping trips. Certainly, the prevalence of small shopping trips means that retailers may benefit from removing barriers that constrain or slow-down shoppers. Initiatives that support shoppers making quick or small trips, such self-check stations improve customer satisfaction (Orel and Kara, 2014). Further initiatives to support small trips, such as specific convenience sections, express

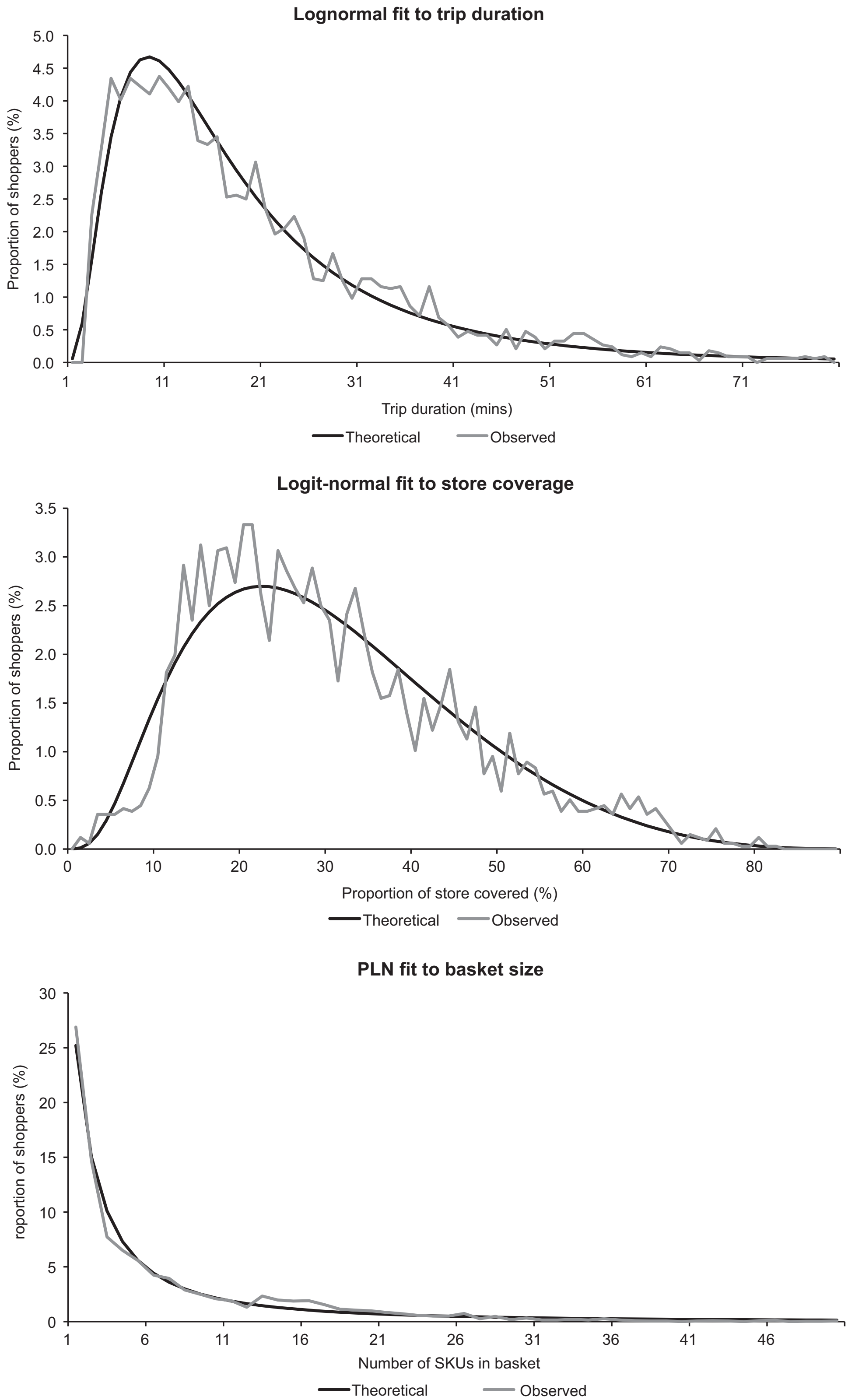

Fig. 3. Example of model fit for a supermarket.

lanes, and fast payment solutions should be explored: shoppers making quick trips may spend up to 8% of their time in a store at or near the checkout, possibly causing frustration for shoppers (Dorsey et al., 2016), and wasted opportunities for retailers if these areas are not adequately merchandised.

This knowledge can assist retailers in judging the effectiveness of marketing strategies and in-store activities in influencing trip behaviors. Having benchmarks for 'normal' retail outlets enables retailers to identify stores that are under- or over-performing. For example, deviation toward trip congruity (when more trips look alike) may be an indication of a better performing store that directs shopper flow through the main pathway. Having robust benchmarks enables such

Table 4
Model parameters and fit statistics (lognormal for trip time; logit-normal for store coverage; Poisson lognormal for the number of products).

	Outlet	Trip time in minutes			Proportion of store covered			Number of products purchased		
		μ	*σ*	*Theil's U*	*μ*	*σ*	*Theil'sU*	*μ*	*σ*	*Theil's U*
US supermarkets	Store A	2.92	0.56	0.10	−0.80	0.24	0.08	0.95	2.49	0.04
	Store B	2.78	0.68	0.08	−0.41	0.34	0.09	1.45	1.49	0.08
	Store C	2.91	0.66	0.09	−0.55	0.33	0.10	1.30	1.56	0.11
	Store D	2.73	0.59	0.08	−0.28	0.38	0.12	1.41	1.43	0.10
	Store E	3.13	0.61	0.08	−0.19	0.37	0.09	1.62	1.08	0.11
	Store F	2.44	0.68	0.08	−0.33	0.32	0.11	1.39	1.32	0.07
	Store G	2.72	0.73	0.07	−0.39	0.33	0.10	0.54	1.91	0.05
	Store H	2.89	0.60	0.12	−0.50	0.29	0.09	1.26	1.21	0.08
	Store I	2.31	0.61	0.08	−0.59	0.34	0.09	1.18	1.11	0.09
	Store J	2.85	0.63	0.16	−0.48	0.29	0.12	0.80	1.20	0.11
	Store K	2.92	0.53	0.08	−0.31	0.23	0.08	1.12	0.78	0.11
Average US super		***2.78***	***0.63***	***0.09***	***−0.44***	***0.31***	***0.10***	0.10	***1.42***	***0.09***
AU super	Store A	2.63	1.00	0.15	N/A	N/A	N/A	3.57	1.77	0.11
	Store B	2.52	0.94	0.19	N/A	N/A	N/A	1.75	1.61	0.03
	Store C	2.92	0.91	0.10	N/A	N/A	N/A	1.82	1.61	0.03
	Store D	2.64	0.97	0.09	N/A	N/A	N/A	1.54	2.00	0.04
	Store E	3.09	1.01	0.16	N/A	N/A	N/A	N/A	N/A	N/A
Average Au super		***2.76***	***0.97***	***0.14***	N/A	N/A	N/A	***2.17***	***1.75***	***0.05***
UK super	Store A	3.17	0.54	0.07	−0.95	0.28	0.07	2.32	1.29	0.02
US hyper	Store A	3.39	0.68	0.09	−1.00	0.30	0.09	0.79	2.68	0.07
	Store B	3.49	0.60	0.15	−0.61	0.23	0.10	1.21	1.46	0.11
China hyper	Store A	3.75	0.46	0.05	N/A	N/A	N/A	N/A	N/A	N/A
Average all h & s		***2.91***	***0.70***	***0.10***	***−0.53***	***0.30***	***0.09***	0.08	***1.56***	***0.08***
AU liquor	Store A	1.51	0.63	0.18	−0.89	0.33	0.03	−1.32	1.78	0.07
	Store B	1.41	0.73	0.09	−0.90	0.38	0.02	0.52	1.58	0.16
	Store C	1.52	0.81	0.21	−1.04	0.31	0.02	−0.58	1.65	0.12
	Store D	1.36	0.70	0.24	−1.11	0.40	0.04	−1.32	1.86	0.20
	Store E	1.15	0.57	0.08	−1.00	0.35	0.01	−0.76	1.20	0.03
	Store F	1.15	0.68	0.11	−1.03	0.31	0.00	−1.37	1.71	0.06
	Store G	1.13	0.53	0.06	−1.01	0.35	0.00	−1.27	1.34	0.08
	Store H	1.19	0.63	0.14	−1.00	0.38	0.02	−1.08	1.54	0.10
	Store I	1.16	0.58	0.04	−0.96	0.30	0.02	−1.63	1.46	0.03
	Store J	0.91	0.52	0.09	−1.17	0.39	0.01	−1.53	1.61	0.07
	Store K	0.97	0.60	0.15	−1.04	0.39	0.01	−1.77	1.51	0.03
	Store L	1.25	0.57	0.18	−0.94	0.39	0.03	−1.68	1.74	0.07
Average specialty /liquor		***1.23***	***0.63***	***0.13***	***−1.01***	***0.36***	***0.02***	***−1.15***	***1.58***	***0.09***
AU drug	Store A	1.71	0.68	0.15	−0.51	0.26	0.07	0.45	0.42	0.05
	Store B	1.73	0.89	0.19	−0.57	0.36	0.04	0.30	0.48	0.05
	Store C	1.64	0.67	0.14	−0.60	0.28	0.03	0.22	0.70	0.07
	Store D	1.46	0.80	0.13	−0.56	0.35	0.07	0.10	0.51	0.05
	Store E	1.56	0.63	0.09	−0.55	0.34	0.07	−0.11	0.71	0.02
	Store F	1.49	0.55	0.16	−0.61	0.30	0.11	−0.85	1.30	0.06
	Store G	1.22	0.66	0.13	−0.71	0.36	0.05	−0.85	1.17	0.04
Average convenience/drug		***1.54***	***0.70***	***0.14***	***−0.59***	***0.32***	***0.06***	***0.07***	***0.76***	***0.05***
Average small format		***1.34***	***0.65***	***0.13***	***−0.85***	***0.34***	***0.03***	***−0.76***	***1.28***	***0.07***
Average		***2.15***	***0.68***	***0.12***	***−0.71***	***0.33***	***0.06***	***0.31***	***1.41***	***0.07***
Max		***3.75***	***1.01***	***0.24***	***−0.19***	***0.40***	***0.12***	***3.57***	***2.68***	***0.20***
Min		***0.91***	***0.46***	***0.04***	***−1.17***	***0.23***	***0.00***	***−1.77***	***0.42***	***0.02***

factors to identified, tested and managed.

Given the distribution of shopping trips, retailers should cater to people making short or small shopping trips by making it more convenient for shoppers to find the items they are seeking quickly. Although reducing the number of SKUs offered in a store may not always be the solution (Scheibehenne et al., 2010), making product categories easier to find with ‘signpost brands’ may help (Kholod et al., 2011). Secondary displays of top-selling items may also play a role in helping shoppers complete their shopping quickly. However, shoppers' reliance on mental maps (as opposed to physical in-store signage) for stores they regularly shop has led researchers to recommend that changes to store layouts are unlikely to have an immediate positive effect and should be made cautiously (Scamell-Katz, 2012; Sommer and Aitkens, 1982). These findings give evidence-based benchmarks for further research in this space e.g. which layout changes are effective, under what conditions.

These findings also have implications for the design of retail outlets, particularly large ones. There may be a limit to the area shoppers will cover during shopping trips. This limit may be related to the time allotted by shoppers to the task, their need for only a few products, or their expectations regarding how far they will walk on a shopping trip. Descriptive analysis of data from the US supermarkets (n=11) confirmed that less than 25% of trips covered more than 1000 m^2 of a supermarket. Typically, shoppers visited about 600 m^2 of supermarkets, which ranged in size from 2000 to 7000 m^2. Although more research is needed, these findings indicate there is a limit to how far shoppers will walk on a shopping trip, a point that is extremely pertinent to the design of retail outlets.

8.3. Implications for manufacturers

For manufacturers, the key implication of the distribution of trip length and coverage metrics is the need to make it easy and fast for shoppers to find their offers in-store. To this end, it may be worthwhile to pay for positions in high traffic flow areas and/or next to top-selling items to increase the chance of such items being noticed and bought during the short trips that dominate shopping. Understanding the exact value of certain locations is an important topic for future research.

The prevalence of small shopping trips also suggests that the emphasis should be on helping shoppers recognize and find brands quickly by providing visual cues, such as images or colors (see Scamell-Katz, 2012), especially those that are uniquely and prevalently linked to the brand (Romaniuk and Sharp, 2015). When considering stock location changes, the often quick nature of shopping may be important. So too should manufacturers bear this in mind when making pack changes (e.g. ensure their packaging is consistent enough when changes are made, so it is easily found by distracted shoppers, as also recommended by Romaniuk and Sharp (2015)). Testing of instore activations and pack changes is encouraged, and it is hoped that studies such as this facilitate this with norms to help interpret individual study findings.

8.4. Implications for researchers

Much prior shopper research relies on post-hoc claimed behavior and rests on the assumption that shoppers are self-aware. Given the brevity of most shopping trips and long-standing evidence of the problems with self-report data (e.g. Nisbett and Wilson, 1977), research methods and measures that can capture routine and automatic shopping processes (such as observation and eye tracking) would be fruitful for further research. Furthermore, loyalty card data, heavily used in academic research, may skew toward heavier buyers and larger shopping trips/transactions if shoppers are less inclined to scan their cards when purchasing just a few items. Given the number of small/quick trips that shoppers make, this could be a serious limitation. Finally, given that shoppers cover only a small proportion of the store on any single shopping trip, researchers of in-store activations (e.g., in-store advertising) must account for the reach profile of any in-store activation when quantifying response levels.

9. Future research

Our research results identify fundamental patterns of shopper behavior, predominantly using data drawn from developed markets (the US, the UK, and Australia). The generalizability of our results to a store in China indicates similar patterns may exist in developing markets. However, more research is needed to demonstrate applicability in other emerging economies and in less car-dependent countries.

Given the findings of Kahn and Schmittlein (1989) regarding consumers' preferences for shopping on Fridays and Saturdays, further research to confirm that the distribution of shopper metrics is similar across the week would be worthwhile. More work is also needed to understand the effect on in-store behaviors of shoppers in specific conditions that may alter these patterns and have managerial implications in-store (e.g. shopper being accompanied by children or the elderly; and of faster checkout processes/technologies).

While this research focuses on brick-and-mortar retail outlets, there is potential to extend the findings to online shopping (for a relevant discussion see Moe and Fader (2001)). Other areas of shopper behavior that would benefit from systematic, pattern-oriented research across many sets of data including traffic flow within stores (as affected by differences in store layout, e.g., left or right side entrance, split or continuous aisles, and coverage benchmarks for different areas of the store) and retailer and manufacturer initiatives in store (e.g., price offers, promotional displays). Longitudinal observation of individual shoppers as they complete different shopping missions and shop in different retail formats would also be useful in understanding the range of behaviors of shoppers, and consistency of behaviors over time.

The availability of large cross-country and cross-format behavioral data sets provides many opportunities to develop fresh insights into shopper behavior. It also presents substantial challenges in integrating data sets to provide generalizable findings. Further systematic studies will be vital in building a comprehensive and empirically grounded theory of shopper behavior capable of describing shopping trips for different purposes in different countries and retail contexts.

Summary statement of contribution

This paper is important given the size and diversity of data that it collates and describes. Importantly, across different countries and store formats and stores of different sizes it confirms that (i) many shopping trips are short; (ii) shoppers typically only cover a small proportion of the store on any trip, and (iii) the heterogeneity of key behavioral measures (store coverage, number of items bought, and trip duration) is generalizable. It lays the foundations for future empirically grounded theory of shopper behavior and provides benchmarks for retailers and manufacturers to understand their performance.

Acknowledgements

The authors wish to thank TNS Sorensen, TNS and National Pharmacies for the provision of data that made this research paper possible.

Appendix A. Original data sources

	Outlet	Date	N trips	m^2	Proportion of store covered			Trip length minutes			Number of products purchased			
					Med	*Mean*	*St Dev*	*Med*	*Mean*	*St Dev*	*Mode*	*Med*	*Mean*	*St Dev*
Hyper	US Hyper A	2005	2866	14428	12	6	11	30	36	22	1	5	9	11
	US Hyper B	2006	2665	15226	11	6	10	34	38	22	1	5	8	8
	China Hyper A	2012	377658	> 15000	NA	NA	NA	43	47	21	1	5	7	7
Average hyper				***14827***	***12***	***6***	***11***	***36***	***40***	***22***	***1***	***5***	***8***	***9***
US supermarkets	Store A	2005	2779	7263	14	16	7	18	21	13	1	5	10	13
	Store B	2004	2743	3729	29	31	15	16	19	13	1	5	9	9
	Store C	2005	2612	4105	22	25	13	18	22	16	1	5	8	9

	Store D	2003	2683	3252	33	37	18	25	18	11	1	5	8	8
	Store E	2009	2838	2433	41	41	18	23	27	16	1	6	8	7
	Store F	2005	2810	2055	31	34	15	11	14	10	1	5	8	9
	Store G	2005	3361	3247	29	32	15	15	19	15	1	4	7	9
	Store H	2006	2723	3966	24	26	12	17	21	14	1	4	7	7
	Store I	2003	3425	4041	21	23	13	16	12	8	1	4	6	6
	Store J	2006	2905	4150	25	27	12	17	21	14	1	3	5	5
	Store K	2008	2853	2932	32	34	12	18	21	12	1	3	5	4
Average US super				***3743***	***27***	***30***	***14***	***18***	***20***	***13***	***1***	***4***	***7***	***8***
AU super	Store A	2012	17208		Individuals not tracked			15	22	21			14*	
	Store B	2012	6609		Individuals not tracked			12	19	20	1	6	14	12
	Store C	2012	86791		Individuals not tracked			20	27	22	1	7	15	12
	Store D	2012	84675		Individuals not tracked			15	21	20	1	6	15	11
	Store E	2012	17208		Individuals not tracked			26	34	29				
Average Au super								***16***	***22***	***21***	***1***	***6***	***15***	***12***
UK super		2010	18466	3800	20	21	8	26	29	15	2	9	15	15
Average all super				***3748***	***27***	***29***	***13***	***18***	***22***	***16***	***1***	***5***	***9***	***9***
Average all hyper & super				***5331***	***25***	***26***	***13***	***22***	***24***	***15***	***1***	***5***	***8***	***9***
AU liquor	Store A	2003	236	334	11	18	10	3	5	4	1	1	2	1
	Store B	2003	275	–	11	18	11	3	5	5	1	1	2	1
	Store C	2003	58	–	11	15	7	3	6	6	1	1	2	1
	Store D	2003	29	–	11	15	8	3	4	4	1	1	2	2
	Store E	2003	334	252	11	16	8	2	3	3	1	1	2	1
	Store F	2003	307	218	11	14	8	2	4	4	1	1	2	1
	Store G	2003	317	–	11	16	9	2	3	2	1	1	2	1
	Store H	2003	329	–	11	16	9	3	4	3	1	1	2	1
	Store I	2003	294	126	11	16	8	2	3	2	1	1	1	1
	Store J	2003	314	198	11	14	7	2	2	2	1	1	1	1
	Store K	2003	262	61	11	16	9	2	3	3	1	1	1	1
	Store L	2003	143	334	11	16	11	2	3	3	1	1	1	1
Average specialty /liquor				***218***	***11***	***16***	***9***	***2***	***2***	***4***	***3***	***1***	***2***	***1***
AU drug	Store A	2005	139	–	25	25	18	4	6	4	1	1	1	1
	Store B	2005	189	–	8	15	11	4	6	8	1	1	1	1
	Store C	2006	100	–	33	31	12	5	6	5	1	2	2	1
	Store D	2006	185	–	22	29	15	5	8	9	2	2	2	1
	Store E	2006	163	329	22	27	11	5	6	5	1	2	2	1
	Store F	2006	132	–	22	30	14	4	5	5	1	1	2	1
	Store G	2006	184	–	33	30	14	4	5	4	1	1	2	1
	Store H	2006	34		22	27	12	4	5	3	1	1	2	1
	Store I	2006	175	315	22	24	13	2	4	3	1	1	1	1
Average convenience/drug				***322***	***23***	***26***	***13***	***4***	***6***	***5***	***1***	***1***	***2***	***1***
Average all outlets			***15856***	***3339***	***20***	***22***	***12***	***12***	***14***	***10***	***1***	***3***	***5***	***5***

** Obtained from summary transaction log data, other statistics not provided*

Appendix B. Technical description of data-collection methods

RFID tags on shopping carts and baskets recorded the amount of time shoppers spent in a store and their navigation patterns, including the areas of the store visited. The RFID tags emitted location signals at 5-second intervals recorded by in-store receivers. The data were collected using a PathTracker® system that enables the location of each shopping cart to be pinpointed and data about shoppers' navigation patterns, speed of walking, and purchasing to be collected unobtrusively from a large sample of shoppers (i.e., 18,500 shopping trips in four weeks). Numerous researchers have shown its value for understanding in-store behavior (Hui et al., 2009c; Larson et al., 2005).

Bluetooth (BT) tracking of shoppers at store entry/exit points was used for six of the Australian stores to capture the amount of time shoppers spent in a store (Phua et al., 2015). Shoppers carrying mobile phones, headsets, or other equipment broadcasting Bluetooth signals were unobtrusively recorded. Doing so provided a sample of approximately five percent of total shopping trips (i.e., 3880 of 84,000 shopping trips in three weeks of transaction records).

In-person observation of shoppers in store was used in 27 of the Australian stores. The observations were highly structured using a precoded track sheet. Researchers recorded the time individual shoppers entered the store, the time they finished shopping and proceeded through checkout, the number of different items purchased, and the total spent. Observers did not interact with shoppers in any way (nonparticipant observation). The relatively small size of the stores (e.g., 300 m^2) and layout of the shelving in store enabled researchers to make discrete observations of shoppers in their natural environment. Similar observation procedures have been used by others (e.g. Boutillier et al., 1994; Dickson and Sawyer, 1986; Farley and Ring, 1966).

Retailer transaction records (TR) supplemented electronic and in-person tracking data to provide a complete record of the number of items purchased by shoppers. Transaction data (also known as *t-log data*) are typically collected by electronic point of sales systems (i.e., scanners at sales registers) and provide a complete record of the items purchased by individual shoppers. Although other data sources, such as loyalty card data, observational data, and trolley data, exclude some shoppers, transaction records are a complete census.

For two of the Australian stores, every transaction made at point-of-sales terminals over a three-week period was analyzed. For the Chinese hypermarket, every transaction over a six-week period was included, except for bulk transactions in which 50 or more units of the same SKU were purchased (0.4% of transactions). For the US and UK stores, analyses were restricted to transactions that had also been tracked electronically with an RFID-enabled shopping cart or basket.

Appendix C. Definitions of store formats

Definitions of store formats vary across countries (Peterson and Balasubramanian, 2002; Sharp, 2013), so we explicitly detail the categorizations.

Convenience – Convenience stores are outlets characterized by a smaller floor space and limited range of products relative to other retailers, such as supermarkets, although it has been noted that convenience stores are expanding in size, reaching the size of small supermarkets (Nacs, 2013). The convenience stores analyzed in this study were drug stores that carried a range of prescription and non-prescription medicines, health and beauty products, baby products, and such convenience items as tissues, sweets, and hosiery. Store layouts varied.

Specialty – Specialty stores retail a single category or a small selection of categories, such as pet food and pet care products. The specialty stores analyzed in this study were liquor stores that sold wine, beer, spirits, and a limited range of nonalcoholic and snack food items. Typically, products were arranged on low aisles in a grid-like pattern. In Australia, where the data were collected, alcoholic beverages are not generally retailed in supermarkets.

Supermarkets – Supermarkets typically retail a selection of 40,000 grocery products or more, usually in a space of 2000–4000 m^2. The stores studied here span 11 retail brands operating in the UK, Australia (multiple locations), China, and the US (multiple locations). All the stores were traditional grocery stores with aisles laid out in a grid-like pattern and a 'racetrack' around the perimeter.

Hypermarkets – This classification covers very large format retailers selling grocery and non-grocery products (i.e., home wares, electrical goods, hardware, apparel, etc.). Wal-Mart, Fred Meyer, and Carrefour are well-known examples. Our definition of *hypermarket* does not include wholesale or club stores where customers must have a membership to shop (i.e., Costco or Sam's Club).

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