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A data-driven approach to grocery store block layout

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ABSTRACT

Retailers are a major component of almost any supply chain and are the interface between customers and goods. A ubiquitous and important retailing segment is grocery stores, yet almost no analytical work in the block design can be found in the literature. This paper uses a data-driven approach coupled with optimization to address block layout in grocery stores with the participation of Migros, the largest retailer in Turkey. The goal is to develop an effective analytical method for solving realistic grocery store block layout problems considering data which describes revenue generation and adjacency of departments. Historic market basket data is used to characterize certain important aspects that relate to customer sales and these are used in a tabu search meta-heuristic to find layouts which are likely to enhance revenue. To consider the objectives of revenue and adjacency simultaneously, a bi-objective approach is used. A set of non-dominated designs is generated for a decision maker to consider further and the generated designs have been validated with a detailed stochastic simulation model and by the marketing experts at Migros. According to the computational results and the feedback from the industry partner, this approach is both effective and pragmatic for a data-driven, analytic design of grocery store block layouts. Layout designs which improve revenues and desired adjacencies relative to the existing store layouts are identified. While this paper focuses on a single retailer, the approach is general and given that grocery layout is similar worldwide, the method and results should be easily translatable to other retailers.

1. Introduction

Supply chains usually culminate in retailing where the customer selects and purchases goods. Retailers are numerous and found everywhere. Among retailers, probably the most common and uniform type is the grocery store. However, for grocery stores, the literature has largely been restricted to addressing shelf space allocation, that is, determining the amount and placement of individual products. What has been virtually ignored is the design in term of block layout of the store itself. While grocery stores almost always follow a general grid construct with orthogonal aisles, there are still many decisions in layout to be made such as how much space to allocate to each product segment, or category, and where to place the product categories relative to each other and to the projected customer flow through the store.

This paper formulates, models and solves the grocery store block layout problem. This specifies the size and location of the product category areas ("departments"). The goal is to maximize revenue especially that of impulse purchases, where the purchase decision is made spontaneously in the store (Abratt & Goodey, 1990; Kollat & Willet, 1967). Although most customers have predetermined lists prior to shopping, 30–50% of sales come from impulse purchases (Kollat & Willet, 1967; Mishra & Mishra, 2010). A store's layout influences the customer's exposure to goods and thus affects the customer's impulse purchases (Inglay & Dhalla, 2010). According to a recent study from Lu and Seo (2015), store layout influences a shopper's movement and purchasing behavior. Ainsworth and Foster (2017) examine the role of comfort within a goods-based retail settings and results showed that in-store layout significantly influences the shopper's wants and preferences, and ultimately, purchases. Moreover, a well-designed store layout can positively influence store atmosphere, patterns of traffic and operational efficiency (Vrechopoulos, O'Keefe, Doukidis, & Siomkos, 2004). However, balance must occur between stimulating impulse purchases and increasing a customer's path length (Ozcan & Esnaf, 2013). Moreover, certain product categories are usually found in proximity to each other such as fresh fruits near fresh vegetables. Conversely, some product categories are never placed together such as pet food and fresh meat. Considering preferred adjacencies of product categories is an important aspect of grocery store layout along with the overall revenue generated. Thus, we take a bi-objective approach considering both objectives.

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The need exists for developing a systematic procedure of layout planning in retail stores to provide competitive advantages to a retailer (Inglay & Dhalla, 2010). In this paper we take an important first step by developing a layout model for grocery stores and propose a pragmatic and effective solution methodology. We approach this common but challenging problem using data-driven techniques. Using the market basket data (items purchased per customer visit), we established relationships among departments and identified opportunities for increasing impulse purchases. To ensure the relevance of our research, we partnered with a major grocery store retailer, Migros. The company operates a total of 1155 stores in 70 provinces of Turkey, and 41 Ramstores outside of Turkey, spanning a total area of 1,588,189 square meters (Migros, www.migroskurumsal.com). Actual data and insights from Migros, the largest retailer in the country of Turkey, were incorporated throughout.

This research contributes to the literature by: (i) Using a data-driven approach to mine certain key elements of a store regarding purchasing behavior of its customers; (ii) Developing mathematical models which reflect actual grocery store block layout situations; (iii) Optimizing the layout of departments, taking into consideration area constraints and adjacency preferences, by maximizing total revenue, incorporating impulse purchase rates; and (iv) Validating the approach using a combination of detailed stochastic simulation and appraisal by store managers and grocery retail experts.

The rest of the paper is organized as follows: a literature review of facility layout problems, focusing on the retail industry and grocery store layout problems is given in Section 2. Section 3 introduces the demonstration cases - two real grocery stores from Turkey. The data-driven approach is explained in detail in Section 4. Section 4 also contains a description of the simulation modeling of the stores and the tabu search optimization approach for block layout. The computational experience is presented in Section 5. Finally, Section 6 offers conclusions and potential future work based on this research.

2. Background

Facility layout problems are well-known with numerous articles published stretching back to the 1950's (see the helpful reviews of Ahmadi, Pishvaee, & Jokar, 2017; Anjos & Vieira, 2017). Although the number of studies in the manufacturing industry is plentiful (e.g., Che, Zhang, & Feng, 2017; Palubeckis, 2017; Suemitsu et al., 2016; Izadinia & Eshghi, 2016; Saraswat, Venkatadri, & Castillo, 2015; Izadinia, Eshghi, & Salmani, 2014; Taghavi & Murat, 2011) papers that focus on the retail industry are limited. An early paper addressing the retail store layout problem is from Botsali and Peters (2005) where the authors propose a model for a serpentine layout for maximizing revenue by increasing impulse purchases. This approach requires knowing customer shopping lists a priori. Later, Botsali (2007) devises several customer profiles and, for a grid layout, maximizes the expected impulse purchase of customers according to the locations of product categories.

Market basket choice is where customers choose items to buy from different product categories (Russell & Petersen, 2000). Surjandari and Seruni (2010) discover associated products by analyzing market basket data, and then use this information to determine the product placement layout using data from a retail store in Indonesia. The sizes of the departments in this paper are fixed so only the locations of products are chosen. A master's thesis by Peng (2011) addresses the grocery store layout problem by maximizing impulse purchases. The author first defines the must-have items in a grid layout store and uses an algorithm to spread these items across the store to increase impulse purchases. The generated layout is improved by using a simulated annealing heuristic. In this study, all the aisles are in a grid and the size of the departments are assumed to be fixed and equal. Cil (2012) develops a layout for a supermarket by clustering the products around customer buying habits through analyzing the transaction database. The author improves the layout by changing the locations of the departments but not their areas, which are fixed. A study from Aloysius and Binu (2013) presents an approach to product placement in supermarkets using the PrefixSpan algorithm. This is a data mining technique used to explore frequent patterns in the shopping lists of customers. The authors aim to maximize impulse purchases by using market basket data analysis. They test their approach on a small dataset.

A model and solution approach for the design of the block layout of a single-story department store with a racetrack layout is presented by Yapicioglu and Smith (2012a, 2012b). The layout is evaluated by the revenue generated by departments and adjacency satisfaction. A general tabu search optimization framework for the model with variable department areas and an aisle network with non-zero area is devised and tested. Another publication of Yapicioglu and Smith (2012a, 2012b) proposes a bi-objective model for the same problem. Adjacency maximization and revenue maximization are the two objectives of the model. A multi-objective tabu search and multi-objective genetic algorithm are used separately to solve the problem. The performance of these two heuristics is evaluated and compared. According to the results, it is suggested that the multi-objective tabu search is a better choice because of its ability to exploit the neighborhood structure of the model. We use a similar tabu search heuristic herein.

Another related example to grocery store block layout is from Ozcan and Esnaf (2013) which considers bookstore layout. The authors develop a mixed integer mathematical model then use both tabu search and genetic algorithm based heuristics to design a bookstore layout with 30 products and 137 shelves. Their model considers the special requirements of bookstore shelves and association rules are used for the determination of the position of books in a grid layout.

A recent study from Pinto, Soares, and Brazdil (2015) combines regression models and the metaheuristic particle swarm optimization to recommend space distributions of product categories within a retail store. The main goal of the model is maximizing sales. The model is demonstrated with an empirical study and the results show that it is able to provide space recommendations considered useful and interesting by business specialists. Bhadury, Batta, Dorismond, Peng, and Sadhale (2016) develop a p-dispersion model to optimize the placement of items in a retail store setting. In this paper, item placement is done with the objective of maximizing the total profit earned from the sale of impulse items and real-world data is taken from a grocery store in the western region of New York. The authors use simulated annealing to optimize the model. There are some limitations. They confine the layout to a grid only and the dimensions of the departments are assumed equal sized or fixed.

The effect of retail promotions on customer traffic is studied by Epstein, Flores, Goodstein, and Milberg (2016) and an analytical approach based on a Poisson model with effect parameters such as time of the day, day of the week, week of the month, secular trends and others, to capture sources of systematic variability is used and the method is illustrated with a case study from Chile. Altuntas (2017) proposes a data mining algorithm to rearrange the layout of a store and develops software to determine the associations between product groups. The approach is demonstrated with a case study from Turkey. Although the algorithm works well in mining the purchasing records, the method has some limitations such as ignoring the space allocation to departments and ignoring the product placement.

When we look at the overall literature, the number of papers pertaining to grocery store layout is quite limited and the data-driven aspects are not well utilized. Furthermore, there have been significant limitations such as considering the store solely as a 'grid' layout and considering only equal area departments. However, in actuality, grocery stores generally have a mixed layout with both grid and racetrack elements with varying sizes of departments. Another important aspect of this paper is exemplifying the relationship between the store layout and data-driven consumer behavior. There are retail management papers that emphasize this point however they consider more qualitative

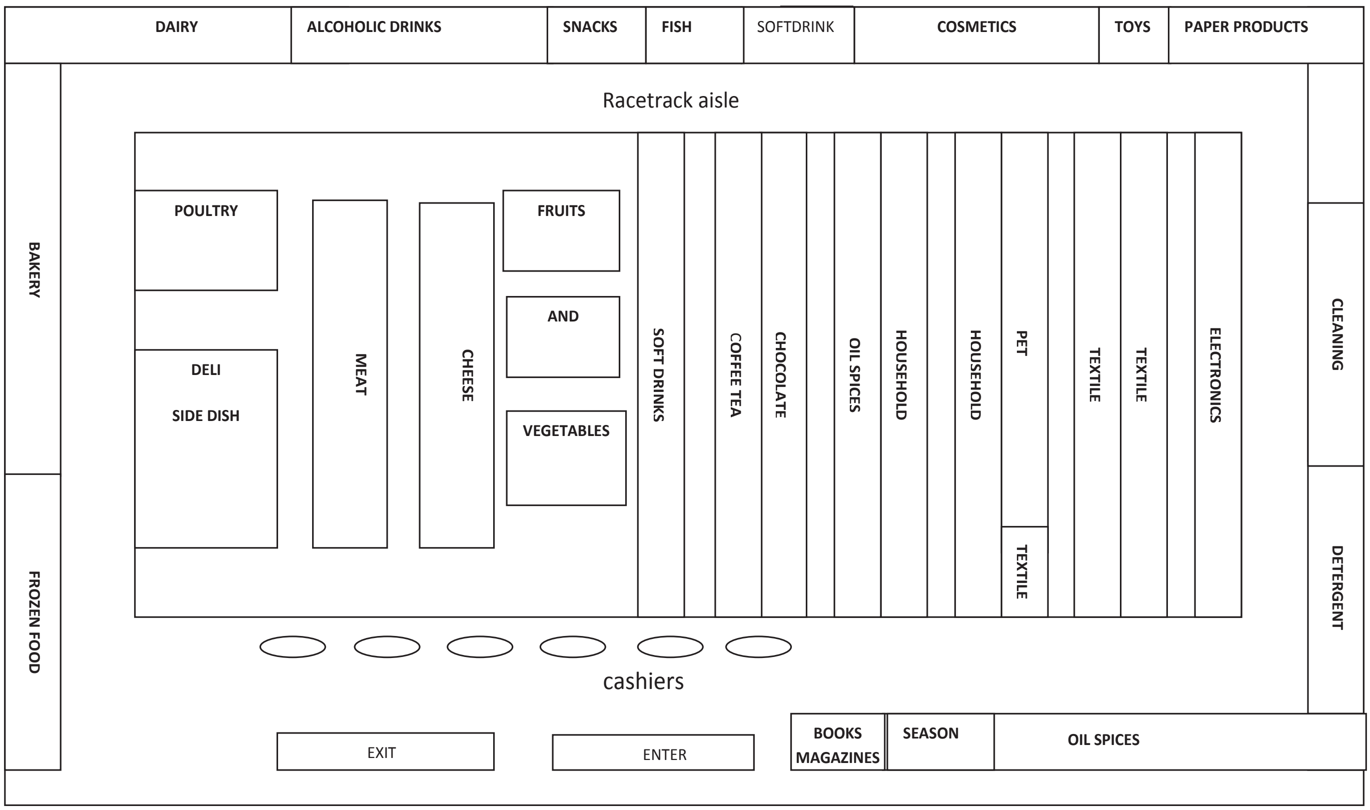

Fig. 1. The layout of the 2M Migros store.

factors and do not enable an analytic approach. Three significant differences between this paper and the existing literature are: (i) Permitting a realistic form to the department layout (a racetrack surrounding a grid), (ii) Allowing the departments to vary in size according to revenue maximization and considering desired adjacencies and constraints on certain locations of departments, and (iii) Devising data-driven methods to relate sales to a customer's path through the store.

3. Demonstration cases

We demonstrate our approach using two actual case studies – two quite different sizes of Migros stores in Istanbul, Turkey. The first store was chosen by the Migros marketing and planning staff as being most typical and general of their smaller stores. This is a middle sized grocery store (1200 square meters, and known in Migros parlance as a 2M store) located in a shopping mall (in Turkey, many grocery stores are located in shopping malls). It has eight straight aisles, a racetrack aisle, and one entrance and one exit as shown in Fig. 1. The second store is also located in Istanbul but in less urban area and it is the largest type of store with 4800 square meters and is termed a 5M Migros. It has one racetrack aisle and 52 grid aisles. Different from the 2M store, the bakery department serves as a café shop with two entrances from two sides of the store. We model each store as a combined grid/racetrack layout with different sizes of departments where the height and depth of all departments are identical but the length varies. All departments have a minimum area in order to properly display essential products. In the grid section, departments face each other in pairs separated by an aisle as found universally in such stores.

For all Migros stores, the company's financial department collects revenue data in 25 categories as shown in Table 1. Note that the "household" category includes seasonal non-food, the "oil and spices" category includes beans and lentils, the "soft drinks" category includes juices, and the "toys" category includes products for pets. These constitute the 25 departments which we will size and place with our data-driven optimization approach.

Table 1
Departments in a Migros store.

	Product category
1	Alcoholic Drinks/Tobacco
2	Bakery
3	Books/Magazines
4	Cheese/Olives
5	Chocolate/Cookies
6	Cleaning Products
7	Cosmetics
8	Dairy/Milk/Yogurt
9	Deli/Side Dishes
10	Detergents
11	Electronics
12	Fish
13	Frozen Foods/Eggs
14	Fruits/Vegetables
15	Household (Seasonal Non-Food)
16	Meat Section
17	Oil/Spices (Beans/Lentils)
18	Organic Fruits/Vegetables
19	Paper Products
20	Poultry
21	Snacks/Nuts
22	Soft Drinks/Juices
23	Tea/Sugar/Canned Food/Breakfast
24	Textile/Shoes
25	Toys/Pet

4. Methodology: Data-driven approach using the market basket data

To establish the relationships among departments and revenue, we evaluated the market basket data collected using association rule mining (also known as affinity analysis). From the findings of this analysis, we developed an adjacency matrix for the departments which gives the preferences for pairwise department proximity. The adjacency forms one of the two objectives. Market basket analysis uses data mining to identify co-occurrence relationships among groups of products, individual items, or categories (Aguinis, Forcum, & Joo, 2013). In retail enterprise analysis and modeling, affinity analysis of the market basket data is used to understand the purchase behavior of customers.

While each store is different, the market basket analysis methodology developed herein to generate adjacency preferences is general and should be applicable, with few modifications, to a wide range of grocery stores (and other retailers). To investigate the relationships among products, a large, randomly selected sample of transactional data of the customers was obtained and analyzed. The primary goal of the analysis is to find which products are sold together to develop an adjacency matrix based on actual sales characteristics of the store.

4.1. Association rules

"Association rule mining is one of the most important fields in data mining and knowledge discovery in databases" (Chen, Wei, Liu, & Wets, 2002). Association rules specify the percentage of consumers who buy product A and also buy product B (Tan & Kumar, 2005). The three standard measures used to understand the presence, nature and strength of an association rule are *lift*, *support* and *confidence* (Berry & Linoff, 2004; Zhang & Zhang, 2002). Lift provides information on whether an association actually exists. If the value for lift suggests an association rule exists, the support value is relevant. Support is the actual probability that a set of items co-occurs with another set of items. Then, confidence is computed, which is the probability that a set of items is bought given that another set of items has already been bought (Aguinis et al., 2013). Lift is analogous to statistical significance testing and is defined as $\frac{P(A \cap B)}{P(A) * P(B)}$. Support is defined as $P(A \cap B)$ and is the probability that A and B co-occur. It calculates the frequency of the rule within transactions. Confidence, defined as $\frac{P(A \cap B)}{P(A)}$, is the probability that a customer will choose a set of items, given that this customer has already chosen another set of items. It denotes the percentage of transactions containing A which also contain B.

In the literature, there have been different minimum threshold values for the support level and the confidence level. For example, Goh and Ang (2007) designated 1% as the minimum support level and 40%, 50%, and 60% as three threshold levels for confidence values. Yang, Tang, and Kafatos (2007) used minimum cut off values of 1.3% for support and 47.6% for confidence. This support value may seem low as Cohen et al. (2001) state, however, the support value's usefulness decreases with very large (e.g., millions of transactions) and rich (e.g., thousands of items) data sets. In these situations, support values can be quite low because the presence of other transactions acts as noise in the data set (Aguinis et al., 2013). In this paper we have selected a minimum lift value of 1.1, a minimum confidence level of 40%, and a minimum support value of 1.5% which are consistent with the literature. A support value is only considered if the minimum lift value and confidence value are satisfied.

Calculations of support, confidence and lift for the Migros 2M store revealed the highest lift value of oil/spices with coffee/tea (2.81). The second highest is poultry with coffee/tea, and the third highest is cheese with bakery. The highest support value is between chocolate and soft drinks (17.7%). Note that lift and support values are symmetric but confidence is not. For example, the oil/spices with coffee/tea confidence value is not the same as the coffee/tea with oil/spices confidence value. Table 2 lists the results which meet the thresholds designated. These results were presented to the staff at Migros and they agreed that the results are consistent with those obtained by their marketing consulting company.

Table 2
Market basket data mining results (ranked by lift value) for the 2M Migros store.

Related departments	Support	Confidence	Lift
Oil/spices - Coffee/tea	5.02%	48%	2.81
Poultry - Coffee/tea	2.25%	47%	2.75
Cheese - Coffee/tea	5.83%	44%	2.57
Cheese - Bakery	6.53%	49%	2.48
Detergent - Coffee/tea	3.80%	42%	2.48
Cleaning products - Coffee/tea	2.30%	42%	2.48
Fish - Fruits/vegetables	1.14%	63%	2.36
Meat - Coffee/tea	4.93%	40%	2.33
Organic fruits - Fruits/vegetables	3.96%	62%	2.31
Poultry - Fruits/vegetables	2.62%	55%	2.04
Meat - Bakery	5.00%	40%	2.04
Meat - Fruits/vegetables	5.48%	44%	1.65
Oil/spices - Fruits/vegetables	4.60%	44%	1.64
Poultry - Chocolate	2.71%	57%	1.50
Coffee/tea - Chocolate	9.55%	56%	1.43
Detergent - Chocolate	4.90%	55%	1.41
Cheese - Chocolate	7.11%	54%	1.38
Paper - Chocolate	5.76%	52%	1.34
Dairy - Chocolate	11.40%	52%	1.31
Cosmetics - Chocolate	5.95%	51%	1.31
Deli - Soft drinks	1.75%	47%	1.17
Chocolate - Soft drinks	17.70%	45%	1.13
Snacks/nuts - Soft drinks	1.55%	45%	1.10

4.2. Adjacency preferences

In many facility layout problems, an adjacency matrix is used to influence the relative locations of departments; one widely used approach involves the use of the REL chart which defines the closeness ratings shown in Table 3 (see, for example, Heragu, 1997 or Tompkins, White, Bozer, & Tanchoco, 2010). We consider departments adjacent if they share a common edge or if they are across the aisle from each other. When the racetrack aisle separates departments, they are not considered adjacent.

The next step in the data analytics involves translating the association rules to a REL chart. A simple algorithm is devised. The highest support, lift and confidence valued department pairs are considered "Absolutely necessary" in closeness score. Using the results in Table 2, department pairs which have a confidence level over 60% are rated as "Absolutely necessary". Department pairs that have a confidence level between 60% and 55% are rated as "Especially important". Department pairs that have a confidence level between 55% and 40% and also satisfy the minimum lift and support values are rated as "Important". Of course, these values can be adjusted as desired but the method remains the same. The approach is not very sensitive to the exact thresholds used for the REL ratings.

Along with the purely data-driven approach, we incorporated the expertise and preferences of the store manager, such as locating the fish department close to the fruit/vegetables department. The manager states that this will make customers spend time in the fruit/vegetables department while waiting for the preparation of their fish orders. He also recommends that the textile and the cosmetics departments be in close proximity as they are especially enticing to women customers.

Table 3
Typical adjacency scores for a REL chart.

Rating	Definition	Value
A	Absolutely Necessary	125
E	Especially Important	25
I	Important	5
O,U	Ordinary Closeness	0
X	Undesirable	−25
XX	Prohibited	−125

Table 4
Adjacency matrix, c_{ij}, (symmetric and only non-zero entries shown).

	Department	4	5	6	8	9	10	11	12	13	14	16	17	18	19	20	21	22	23	24	25
1	Alcoholic Drinks/Tobacco	5	25	−25		25	−25	−25	5			5				5	25	5			−25
2	Bakery	25		−25			−25	−25							−25	−25				−25	−25
4	Cheese/Olives		25	−25			−25	−25							−25				25		−25
5	Chocolate/Cookies			−25			−25									25		25	25		
6	Cleaning Products				−25	−25	−25	−25	−25	−25	−25	−25		−25		−25	−25	−25	−25		25
7	Cosmetics								−25	25	−25	−25				−25				25	
8	Dairy/Milk/Yogurt						−25	−25							−25						−25
9	Deli/Side Dishes						−25					5		−25	25					−25	−25
10	Detergents								−25	−25	−25	−25		−25	25	−25	−25	−25			
11	Electronics								−25					−25							
12	Fish										125									−25	−25
13	Frozen Foods/Eggs																				−25
14	Fruits/Vegetables												5	125		25					−25
16	Meat Section												5		−25	25			5		−25
17	Oil/Spices (Beans/Lentils)															5			125		
20	Poultry																				−25
21	Snacks/Nuts																	5			
22	Soft Drinks/Juices																		5	−25	

Finally, he insists that food products cannot be located next to cleaning products or detergent. The REL chart is given in Table 4.

To assess the layout efficiency for adjacency a metric by Yapicioglu and Smith (2012a, 2012b) is used. This measures how well the proposed block layout design performs by calculating the relative difference between the design and a design that perfectly fulfills all adjacency preferences. The layout adjacency efficiency is denoted by ε and its maximum value is 1.

$$\varepsilon = \frac{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}(c_{ij}^{+}x_{ij}) - \sum_{i=1}^{n-1}\sum_{j=i+1}^{n}(c_{ij}^{-}(1-x_{ij}))}{\sum_{i=1}^{n-1}\sum_{j=i+1}^{n}c_{ij}^{+} - \sum_{i=1}^{n-1}\sum_{j=i+1}^{n}c_{ij}^{-}} \tag{1}$$

where

$$x_{ij} = \begin{cases} 1, \text{department } i \text{ is adjacent to department } j \\ 0, \qquad\qquad \text{otherwise} \end{cases}$$

n: the number of departments

4.3. Shelf space allocation and the revenue function

An increase in demand does not relate in a linear manner to an increase in shelf space. The ratio of sales to space allocation is positive but its magnitude decreases as space increases (e.g., Brown & Tucker, 1961; Bultez & Naert, 1988; Eisend, 2014). Since the shelf space allocated to an item influences an item's sales, the revenue function should consider the space elasticity of product categories. Space elasticity measures the relative change in unit sales to relative change in shelf space (Curhan, 1972). Similar to shelf space allocation models, the model proposed in this paper uses diminishing returns in revenue with respect to length (recall that height and depth are fixed throughout). Each department is assigned upper and lower bounds on shelf space and the revenue function is defined using the well-known exponential relationship to model diminishing returns:

$$R_i = r_i s_i^L + r_i (s_i - s_i^L)^{\beta i} \tag{2}$$

$$s_i^L \le s_i \le s_i^U$$

r_i: unit revenue for department i
β_i: space elasticity for department i
s_i : shelf space allocated to department
s_i^L: lower bound of the shelf space allocated to department i
s_i^U: upper bound of the shelf space allocated to department i

In the literature of estimating shelf space elasticities, most studies are data-driven. These include Curhan (1972), Bultez and Naert (1988) and Dreze, Hoch, and Purk (1995). Thurik (1986) considers space elasticity at the store level and draws the conclusion that it is 0.68 for supermarkets and 0.51 for hypermarkets. Irion, Lu, Al-Khayyal, and Tsao (2012) suggest intervals of space elasticity for three categories based on interviews with store managers- [0.06, 0.1] for unresponsive products, [0.16, 0.20] for moderately responsive products, and [0.21, 0.25] for responsive products. Van Dijk, Van Heerde, Leeflang, and Wittink (2004) use data concerning five brands of shampoo from 44 supermarkets from a large retailer in The Netherlands that spanned 109 weeks and included information about prices, promotional activities and sales; they found that the shelf space elasticity estimates range from 0.62 to 1.08 with an average of 0.85. Considering this literature, we met with the marketing managers of Migros and estimated the space elasticity β of each department as shown in Table 5.

4.4. Simulation modeling of the store

To validate the approach to estimating revenue from equation (2),

Table 5
Estimated space elasticity of department).

	Department	Space elasticity (β)
1	Alcoholic Drinks/Tobacco	0.95
2	Bakery	0.95
3	Books/Magazines	0.85
4	Cheese/Olives	0.95
5	Chocolate/Cookies	0.95
6	Cleaning Products	0.85
7	Cosmetics	0.95
8	Dairy/Milk/Yogurt	0.95
9	Deli/Side Dishes	0.95
10	Detergents	0.85
11	Electronics	0.75
12	Fish	0.65
13	Frozen Foods/Eggs	0.75
14	Fruits/Vegetables	0.95
15	Household (Seasonal Non-Food)	0.85
16	Meat Section	0.75
17	Oil/Spices (Beans/Lentils)	0.95
18	Organic Fruits/Vegetables	0.45
19	Paper Products	0.95
20	Poultry	0.45
21	Snacks/Nuts	0.85
22	Soft Drinks/Juices	0.85
23	Tea/Sugar/Canned Food/Breakfast	0.95
24	Textile/Shoes	0.75
25	Toys/Pet	0.65

we developed a discrete event simulation of the 2M store using the market basket data. Since retail store processes involve many stochastic variables such as quantity purchased and customer routing, discrete-event simulation is an appropriate methodology for this environment (Bruzzone & Longo, 2010). For each customer arriving in the virtual grocery store, the simulation model dynamically creates a shopping list by considering the visit probabilities calculated by the market basket data from the store. We chose to use triangular distributions for amount spent and visit probabilities by department. The customer walks through the store using the shortest path and picks up the items on their list. A product's impulse rate determines the likelihood that the shopper will make additional (impulse) purchases along the route.

Because of lack of data concerning which purchases in the market basket are planned or impulse, we used impulse rates of the departments estimated by the store management. We used the impulse buying tendency scale from (Verplanken & Herabadi, 2001), a 5-point Likert-type scale ranging from 1 (very low) to 5 (very high). Knowing the average purchased amount per each department from the market basket data, it is assumed that the customer will most likely spend 10 percent of this amount times the impulse rate. For instance, the average purchased amount for alcoholic drinks/tobacco is 2.94TL (Turkish Lira) and this department has an impulse rate of 3. The average impulse amount for this department would total 3 * 2.94 * 0.10 = 0.88TL. Using a triangular distribution, the extra amount would appear as (0.2, 0.88, 2) TL in the simulation. The minimum and maximum values are assigned by considering the average spent amount. Whenever a customer passes by a department, a random number is generated between 0 and 1. This number is compared to a threshold established for that department based on its likelihood of impulse purchases. For instance, there is a threshold value of 0.1 for an impulse rate of 1 and a value of 0.8 for impulse rate 5. Threshold values are shown in Table 6 and the impulse rates are shown in Table 7. A comparison of the actual revenue by department and the simulated expected revenue by department is given in Table 8 and it is evident that they are quite similar.

Our simulation is in statistical agreement with the actual sales data, and it was also vetted by the marketing experts at Migros. A one-way analysis of variance (ANOVA) is used to determine if there are any significant differences between the means of two or more independent groups. As seen from the results of the ANOVA test in Table 9 we can conclude that there is no statistically significant difference between the actual store data and the simulation models at 99% confidence. The simulation model is used for detailed analysis of the recommended store designs. While the deterministic objective function (Eq. (2)) does not replicate the stochastic simulation precisely in every case, the two are very congruent. Since it is not practical to run a stochastic simulation during the block layout design optimization due the computational effort required, it is important to know that this straightforward deterministic model of revenue has enough fidelity with the actual store.

4.5. Tabu search for block layout design of grocery stores

To design the block layout, that is, to specify the size (length) of each department and its location, we use a tabu search (TS) metaheuristic. We have selected TS because the block layout model is combinatoric and TS has been used efficiently and effectively for many discrete optimization problems. To properly consider the concerns of the grocery store decision makers, we approach the design with two objectives – revenue generation and adjacency satisfaction - and TS can

Table 6
Impulse purchase thresholds.

Impulse Rate	Thresholds
1	0.1
2	0.3
3	0.5
4	0.7
5	0.8

Table 7
Impulse rates of departments for the simulation of the 2M store.

	Department	Impulse Rate
1	Alcoholic Drinks/Tobacco	3
2	Bakery	5
3	Books/Magazines	3
4	Cheese/Olives	3
5	Chocolate/Cookies	5
6	Cleaning Products	2
7	Cosmetics	5
8	Dairy/Milk/Yogurt	4
9	Deli/Side Dishes	4
10	Detergents	2
11	Electronics	1
12	Fish	3
13	Frozen Foods/Eggs	1
14	Fruits/Vegetables	4
15	Household (Seasonal Non-Food)	2
16	Meat Section	2
17	Oil/Spices (Beans//Lentils)	4
18	Organic Fruits/Vegetables	1
19	Paper Products	2
20	Poultry	2
21	Snacks/Nuts	4
22	Soft Drinks/Juices	3
23	Tea/Sugar/Canned Food/Breakfast	4
24	Textile/Shoes	3
25	Toys/Pet	1

Table 8
The comparison of the 2M store revenue data with the simulation results for one month.

Department	Actual Value	Simulated Value
Alcoholic Drinks/Tobacco	13165.77	13074.94
Bakery	5629.22	5511.91
Books/Magazines	2164.4	2146.86
Cheese/Olives	9500.07	9485.10
Chocolate/Cookies	10793.50	10772.28
Cleaning Products	1606.84	1655.57
Cosmetics	7329.55	7512.22
Dairy/Milk/Yogurt	6193.63	6272.31
Deli/Side Dishes	5188.10	5191.20
Detergents	4602.05	4682.28
Electronics	2075.26	2074.68
Fish	2120.22	2066.59
Frozen Foods/Eggs	3113.27	3128.46
Fruits/Vegetables	7525.43	7783.82
Household (Seasonal Non-Food)	3323.67	3383.79
Meat Section	6734.24	6653.90
Oil/Spices (Beans/Lentils)	4307.47	4229.97
Organic Fruits/Vegetables	2173.00	2192.54
Paper Products	5863.68	5859.18
Poultry	2518.21	2594.55
Snacks/Nuts	2660.95	2664.02
Soft Drinks/Juices	4108.07	4011.28
Tea/Sugar/Canned Food/Breakfast	7481.34	7492.80
Textile/Shoes	644.42	674.47
Toys/Pet	923.00	874.49
Meat Section	**121972.31**	**121989.20**

Table 9
Store data (2M) versus simulation.

	Sum of Squares	df	Mean Square	F	Sig.
Between Groups	11301.208	1	11301.208	0.001	0.973
Within Groups	4.851E8	48	1.011E7		
Total	4.851E8	49			

be readily adapted to such purposes. The main motivation behind the idea of bi-objective optimization is the conflicting structure of revenue and adjacency. We use the multinomial tabu search (MTS) algorithm developed by Kulturel-Konak, Smith, and Norman (2006) which is a true multi-objective search to identify the Pareto set of non-dominated solutions. The details of the TS algorithm are as follows:

(a) **Solution representation**: The layout of the store is represented by a 3 by 25 matrix since there are 25 departments in each store. The first row of the matrix indicates the bay number assigned to a department. Departments are assigned to a single racetrack bay, which is along the perimeter of the store, or to one of the grid bays (reciprocal aisles). A department can only be assigned to one bay. This is the preference of store management. All bays are arbitrarily numbered. The second row of the matrix shows the ordering of the departments starting (arbitrarily) from next to the exit and continuing counter clockwise around the racetrack bay, or for the grid aisles, the ordering starts from top to bottom. The third row specifies the length of department in the bay (recall that widths and heights of the racks are assumed to be identical across all departments so only length impacts size). The inputs to the algorithm include the bay lengths, the minimum and maximum lengths (i.e., sizes) of the departments, and, from the data mining, the unit revenues per length of departments, the β values of the departments, and the adjacency matrix.

(b) **Constraints**: Length constraint: Departments must be within the range of their minimum and maximum lengths – and the total of department lengths must equal the total length available; and Adjacency constraint: Departments having REL score of -25 cannot be placed next to each other.

(c) **Initial solution**: First, take a randomly-generated department sequence string (second row). Then, for that department string, generate all possible bay strings (first row). The constraint is that total minimum lengths of departments in the bay ≤ bay length ≤ total maximum lengths of departments in the bay. The algorithm searches until no feasible bay strings and unassigned departments exist. In the second step, generate the length string (third row). From all possible bay strings and the given department string, assign the lengths of departments by considering the minimum and maximum length constraints and calculate the total revenue each time. Choose the layout giving the maximum total revenue.

(d) **Move operator:** A swap operator exchanges the location of two departments. The number of solutions reachable using the swap operator equals $n*(n-1)/2 = 25*24/2 = 300$. This move swaps the department sequences and then finds the best bay arrangements and department lengths for that sequence using the approach of step c above.

(e) **Tabu list entries:** The most recently swapped department pairs are stored on the tabu list. This prohibits the pair from being swapped again during its duration on the tabu list. A uniform distribution dynamically changes the size of the tabu list between 15 and 30 entries, a typical method in TS.

(f) **Objective functions:** Randomly alternates between maximizing total revenue (TR) and maximizing the adjacency efficiency, ε.

(g) **Aspiration criterion:** If a solution within the neighborhood has a better objective function value than at least one of the non-dominated solutions, allow a move to that solution even if it is tabu.

(h) **Termination criteria:** First, choose a certain number of iterations (e.g., 500 iterations) as a termination criterion. Then, as a second strategy, if no new non-dominated solutions have been found for 50 consecutive moves, the search terminates. Again, these are typical values in TS.

The summary of the overall optimization process is given in Fig. 2.

5. Computational experience

We solved two actual store layouts – the 2M and the 5M stores. For both, we kept the data mining method and optimization algorithm identical. Unique to each case study are the market basket data and the grid structure and dimensions.

5.1. The 2M store

For the 2M store, we found three non-dominated solutions as seen in Fig. 3 along with the current layout seen on the lower left. One has 126,915TL with 0.57 adjacency (maximum revenue), the second has 0.62 adjacency and revenue of 125,145TL and the third with 124,735TL and 0.77 adjacency (maximum adjacency). For this problem, the bi-objective TS is robust to seed (we used 10 seeds, that is starting solutions, for each run) and to setting of the probabilities of each objective function becoming active. All yielded the same results. Tables 10, 11 and 12 show these three non-dominated solutions. All three significantly improve upon the current layout both in terms of adjacency and revenue.

This matrix in Table 10 can be interpreted as follows:

- In the first row of the matrix, 12 is the racetrick aisle. Department 2, bakery, will be initially located by the entrance and the length of that department is 16 m as shown in the third row. Department 4, cheese and olives, will be located next to bakery with a length of 11 m.
- The rest of the matrix can be read in the same way and Fig. 4 represents the layout in Table 10.

When we compare these proposed store layouts with the current 2M store layout, there are differences. According to the data mining results of association rules, there is a close relationship between the oil/spices department and the coffee/tea department but they are not located next to each other in the current store. However, in the second and third layouts, these two departments are neighboring. Another output of the association rules is the strong relationship between the bakery and the cheese departments. Although in the current layout these departments are not next to each other, all three proposed layouts locate them next to each other. Guided by the high unit revenues per length, the alcoholic drinks department is enlarged to 22 m from 18 m and the chocolate/cookies department is enlarged to 28 m from 23 m in Layout 1. The household and oil/spices departments are reduced in size to make room for these two enlargements. Conversely, the main goal of Layout 2 is improved adjacency so the chocolate/cookies department is reduced to 19 m to locate this department next to the soft drinks department. As seen expected, a trade-off occurs between increased revenue and enhanced adjacency. Among the Pareto efficient solutions, the decision-maker should choose the best solution, but perhaps a good choice might involve the layout with the largest revenue just before a significant decrease in adjacency. In our Pareto archive, the middle solution may not be a good option since the adjacency score of the maximum revenue layout and middle solution are similar.

5.2. The 5M (Hypermarket) store case study

In this store, the same department categories are used however the hobby department includes garden and flowering products and automobile maintenance products. The number of departments and their names are slightly different than in the 2M store. Also, four departments (electronics, hobby, household and textile/shoes) are split among two areas each in the current store. Furthermore, the company manager insisted that the dairy products, cheese and olives and meat and poultry departments not be relocated because of the refrigeration system. As a company policy, the fruits and vegetables department is located in the corner for 5M stores and the fish department is next to them, similar to

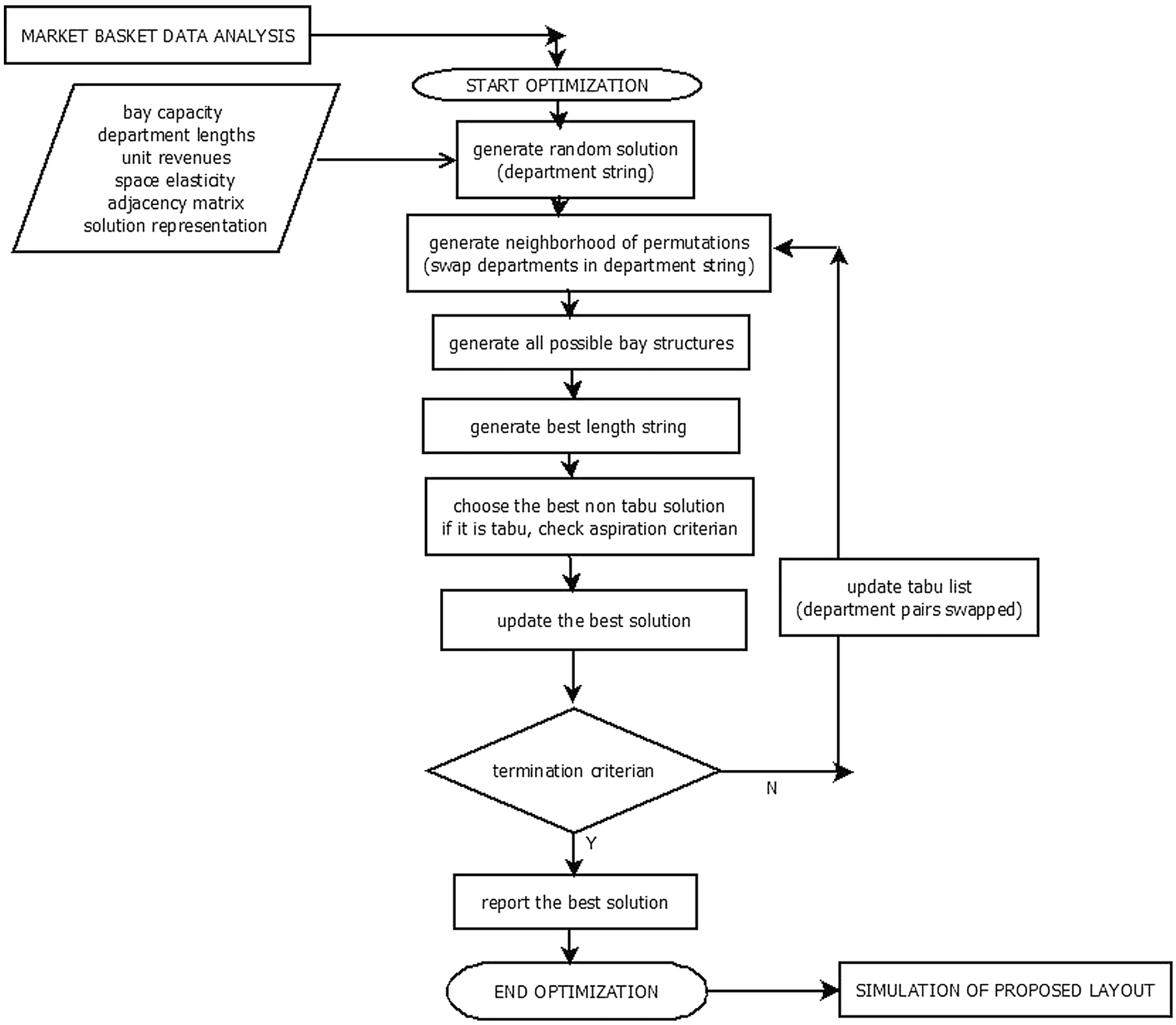

Fig. 2. Overall block layout optimization procedure.

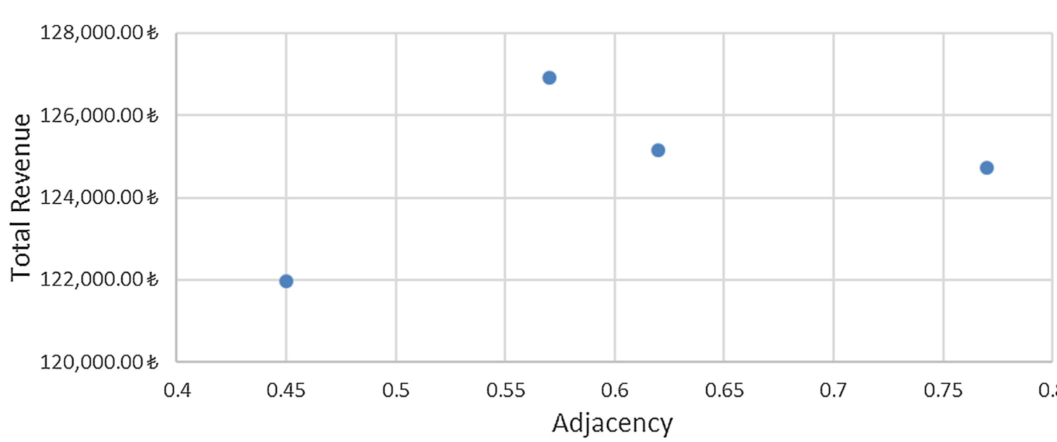

Fig. 3. Pareto set of block layout designs for the 2M store along with the current layout (lower left) which is clearly dominated by our solutions.

Table 10
Solution with adjacency 0.57.

12	12	12	12	12	12	12	12	12	12	1	2	3	3	4	5	5	6	7	8	9	10	10	11	11
2	4	18	14	12	15	17	21	1	5	23	22	20	9	8	13	16	24	7	19	10	6	25	3	11
16	11	6	18	6	24	22	7	22	28	19	19	6	13	19	7	12	19	19	19	19	13	6	10	9

Table 11
Solution with adjacency = 0.77.

12	12	12	12	12	12	12	12	12	12	1	2	3	3	4	5	5	6	7	8	9	10	10	11	11
2	4	23	17	15	18	14	12	1	21	22	5	20	9	8	13	16	24	7	19	10	6	25	3	11
16	11	20	29	24	7	18	6	22	7	19	19	6	13	19	7	12	19	19	19	19	13	6	10	9

Table 12
Solution with adjacency = 0.62.

12	12	12	12	12	12	12	12	12	12	1	2	3	3	4	5	5	6	7	8	9	10	10	11	11
13	17	23	4	2	15	14	12	21	1	22	5	20	9	8	18	16	24	7	19	10	6	25	3	11
11	25	20	11	16	24	18	6	7	22	19	19	6	13	19	7	12	19	19	19	19	13	6	10	9

the 2M store. We treated these departments as monuments, that is, fixed in location.

As with the 2M store, the market basket data was analyzed by using association rules. One year of sales data, 1,750,643 transactions, was collected from company and the lift, support and confidence values were calculated. These values are incorporated to the adjacency matrix similar to that of the 2M store. According to the analysis, there is a strong relationship between the hobby and electronics departments and the cosmetic and textile departments. We used the same TS with the same parameters as for the 2M store and found four non-dominated solutions. Fig. 5 shows the Pareto set of solutions along with the current store layout (lower left) and Table 13 gives the details of each of these new designs relative to the existing one.

According to the analysis of market basket data and the adjacency matrix, there is a close relationship between the textile and cosmetics departments, the household and detergent departments, alcoholic drinks and soft drinks, and the hobby and electronic departments. The locations of the chocolate/cookies, soft drinks and canned food departments are preferred to be closer to each other. In the current layout, the chocolate/cookies and paper products departments are split up although they are in the same bay. These departments are combined in the proposed layouts.

In Layout A, revenue is maximized but still the adjacency increases from 0.59 in the current layout to 0.70. The basic difference is the racetrack aisle. The breakfast, chocolate/cookies, canned food and tea/sugar departments are all located in the racetrack. The textile departments are combined and the cosmetic department is located next to it in the third bay.

In Layout B, adjacency is maximized. The hobby and electronics departments are located next to each other, the household and detergent departments are next to each other, and the soft drinks, alcoholic drinks and snacks/nuts departments are consecutive. Textile and cosmetics are also next to each other. The total revenue is slightly less than the first layout however it is still three percent better than the current layout's revenue.

Layout C is a compromise design. The only difference from Layout B is combining the electronics departments into one and locating it next to the hobby department. This increases the revenue slightly. Finally, Layout D also has good total revenue and adjacency however the alcoholic drinks, snacks and nuts, chocolate and cookies departments are located in the racetrack aisle.

When considering these layouts, all four suggested ones improve upon the current 5M layout for both revenue and adjacency. A good choice may be Layout D which has fairly high adjacency but also the second highest revenue among all designs.

6. Conclusions and future research

This research proposes a data-driven approach for the grocery store block layout problem. It contributes to the literature by being the first to take a data-driven approach coupled with a mathematical model capturing the major decision aspects – adjacency, impulse purchases, size of product categories, fixed departments. The model is solved and validated through both a detailed simulation and by the company experts. Results clearly show the value of such an approach –simply by rearranging and resizing the product categories, revenue can be substantially improved.

Mining the market basket data gives insights to help from

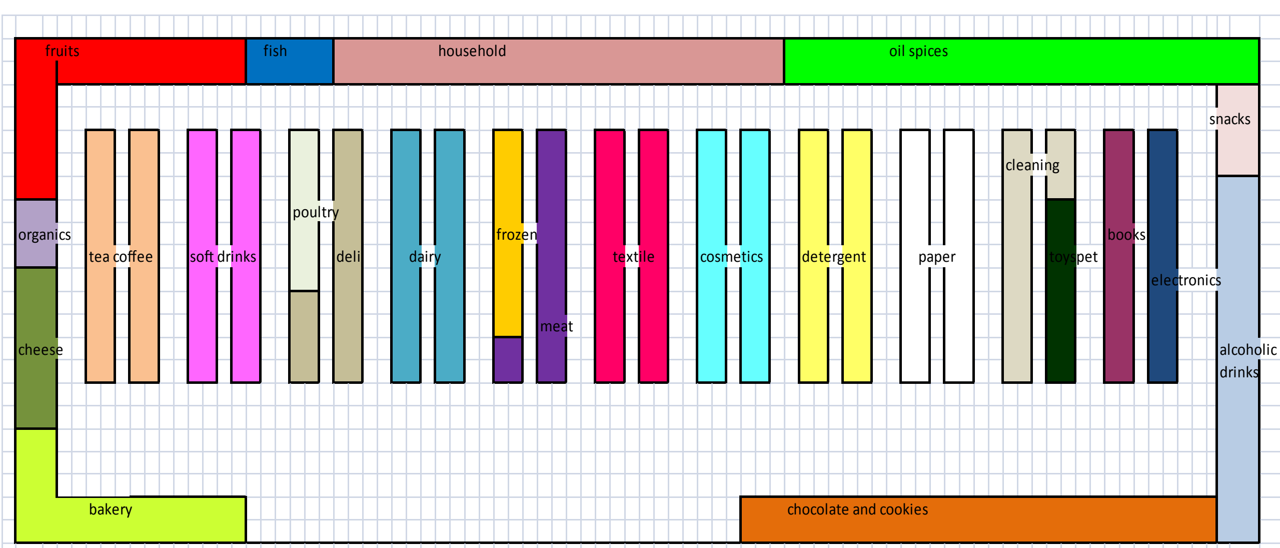

Fig. 4. Layout 1 (adjacency 0.57) of the 2M store.

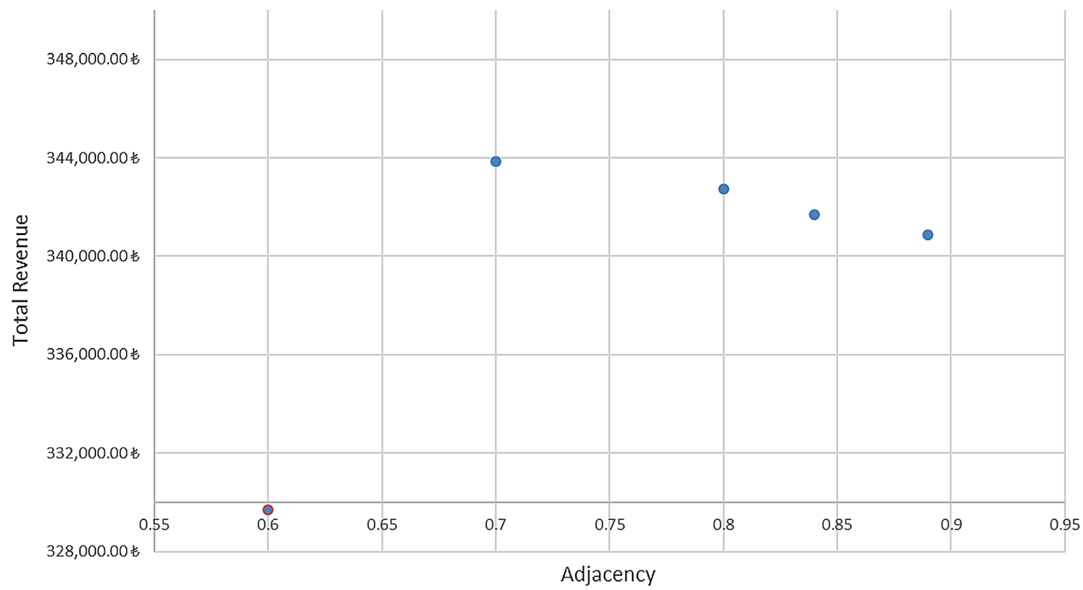

Fig. 5. Pareto set of four new designs for the 5M store along with the current layout (lower left), again showing the clear dominance of our solutions to the existing layout.

Table 13
The proposed layouts and department lengths and total revenue of new layouts.

Department name	Min size	Max size	Unit revenue	Current size	Current revenue	Size A	Revenue A	Size B	Revenue B	Size C	Revenue C	Size D	Revenue D
Alcoholic drinks/tobacco	32	39	697	35	24,407	39	27,196	39	27,196	39	27,196	39	27,196
Bakery (coffee shop)	18	22	680	20	13,599	20	13,599	20	13,599	20	13,599	20	13,599
Books/magazines	41	50	77	45	3482	41	3172	41	3172	41	3172	41	3172
Breakfast	23	28	76	25	1899	23	1747	23	1747	23	1747	23	1747
Canned food	16	20	167	18	3000	19	3167	18	3000	16	2667	19	3167
Cheese olives deli/side dishes	26	32	1558	29	45,173	29	45,173	29	45,173	29	45,173	29	45,173
Chocolate/cookies	43	53	310	48	14,901	53	16,453	53	16,453	53	16,453	52	16,143
Cosmetics	68	83	158	75	11,837	78	12,310	68	10,732	68	10,732	69	10,890
Dairy products	17	21	545	19	10,359	19	10,359	19	10,359	19	10,359	19	10,359
Detergent/cleaning products	65	79	222	72	16,000	79	17,556	79	17,556	79	17,556	79	17,556
Electronics	20	24	467	22	33,628	24	11,209	24	11,209	24	11,209	24	11,209
Electronics – 1	45	55	467	50	0	55	25,685	55	25,685	55	25,685	55	25,685
Fish	9	11	521	10	5205	10	5205	10	5205	10	5205	10	5205
Frozen food/eggs	18	22	195	20	3905	22	4296	18	3515	18	3515	22	4296
Fruits/vegetables/ organics	32	40	573	36	20,613	36	20,613	36	20,613	36	20,613	36	20,613
Hobby	41	51	31	46	1844	41	1271	41	1271	41	1271	41	1271
Hobby – 1	12	14	31	13	0	12	0	12	0	12	0	12	0
Household	40	48	34	44	6586	40	1372	40	1372	40	1372	40	1372
Household – 1	133	163	34	148	0	133	4522	149	5066	149	5066	133	4522
Oil and spices/dried food	72	88	251	80	20,074	88	22,081	88	22,081	88	22,081	88	22,081
Paper products	78	96	158	87	13,741	95	15,005	96	15,162	96	15,162	96	15,162
Pet	9	11	154	10	1542	9	1388	9	1388	9	1388	9	1388
Poultry/meat	23	29	1395	26	36,263	26	36,263	26	36,263	26	36,263	26	36,263
Snacknuts	14	18	718	16	11,484	18	12,920	18	12,920	18	12,920	18	12,920
Soft drinks	39	47	227	43	9745	47	10,652	41	9292	47	10,652	47	10,652
Tea sugar	31	37	294	34	10,000	37	10,882	37	10,882	37	10,882	37	10,882
Textile and shoes	86	106	52	96	6863	86	4505	86	4505	86	4505	95	4977
Textile and shoes – 1	32	39	52	35	0	32	0	36	0	32	0	32	0
Toys	85	103	38	94	3530	85	3192	85	3192	85	3192	85	3192
Total					**329,680**	**1296**	**341,793**	**1296**	**338,610**	**1296**	**339,636**	**1296**	**340,692**
Adjacency					**0.59**		**0.70**		**0.89**		**0.84**		**0.80**

appropriate adjacencies and impulse purchase rates. The bi-objective TS optimization gives the decision maker a small set of non-dominated designs to choose from. Furthermore, using a deterministic space elasticity relationship in the TS is computational efficient and gives results very close to the detailed store stochastic simulation. The TS optimization is not sensitive to the exact form of the space elasticity relationship nor to the settings of the TS parameters. The floorplan designs produced are implementable with minor massaging while capturing the important drivers of unit revenue, impulse purchases, category affinities, adjacency preferences, and space/revenue elasticities.

In the case studies, two different sized and structured stores are

Table 14
Comparisons of 2M and 5M store. The improvements for revenue use the non-dominated solutions with the highest revenue while the improvements in adjacency use the non-dominated solutions with the best adjacency.

2M Store	5M Store
1200 square meters (8 grids and 1 racetrack)	4800 square meters (52 grids and 1 racetrack)
Located in an urban area in a shopping mall	Rural outskirts of the city
One entrance and one exit	Two entrances and two exits
Most frequent item set:chocolate and soft drinks	Most frequent item set: household and detergent
4% revenue improvement	3% revenue improvement
70% improvement in adjacency	50% improvement in adjacency

selected to implement the model. The 2M store was one fourth of 5M store in size and the customers have different shopping behavior since one is in more rural side of the country while the other is urban. Furthermore, there are more additional departments such as hobby, large electronics aisle and a coffee shop typed bakery department found in the 5M store. A comparison of these two store types can be summarized in the Table 14:

As seen from the table, the newly identified designs significantly improved upon the current store design in both adjacency and revenue. It is evident that a data-driven approach to this problem in the end user supply chain has strong merit.

There are also some limitations of this paper. We assumed a slightly different layout than the physical store. The total shelf length of the store model is the same as the physical store but the grid aisles are all the same length, which is not strictly true in the physical store. We assume what constitutes adjacency but this could be modified to be more or less stringent. For example, departments on the race track could be considered adjacent to those on grid aisles immediately across. Our revenue versus space elasticity relationships are somewhat ad hoc even though they are based on expert opinion, the literature where possible, and the market basket data of the specific store. Similarly, a more rigorous identification of impulse purchase rates would be desirable. These are difficult challenges that merit considerable study.

This is a first efforts to analytically design grocery store layouts considering impulse purchase rates, departmental adjacency, and space constraints. There are many ways to extend the work. Firstly, we considered only the block layout problem. An extension opportunity would be to combine block layout with the well-known shelf space allocation problem, considering detailed product placement and sizing in the store along with departmental placement and sizing. A second important step forward would be to gather data on how customers traverse through the store. While the market basket data shows what was bought, it does not show everywhere the customer went in the store and the path taken between purchases. This information would be helpful to understand traffic patterns more precisely to better locate high impulse purchase product categories. A third study would be to consider the end caps of the aisles which generally house promotional and seasonal items. Another follow on would be to study stores in other countries. While the aisle design of all grocery stores is very similar, the buying habits of customers differ. The method proposed herein could be used readily for any grocery store which has market basket data, but the results designs would change from one region or country to another. This could be an interesting sociological study. Finally, this research could be extended to designing online grocery stores and comparing the results of virtual stores with conventional stores.

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