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The Evolution of Corporate Location Planning: A Survey Approach

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Abstract

The unprecedented growth of big data has provided opportunities for the enhancement of retail location decision-making (RLDM) activities. Through a survey of Canadian retail location decision makers, this study examines the current state and progress in: (1) the type and scale of location decisions that retail firms undertake; and (2) the availability and use of geospatial big data and analytics within the decision-making process. The study finds significant increases in the usage of geospatial big data and analytics within corporate location planning. RLDM approaches have expanded to include new data sources, such as social media and mobile location data. With technology redefining consumption behaviours, the retail sector is looking to better understand how best to serve consumers in a market experiencing significant changes to the ways consumers shop. With granular level data being integrated into RLDM a skills gap is emerging in terms of handling and analyzing geospatial big data.

1. Introduction

With advancements in data collection allowing for greater potential to generate more holistic insights into consumer behavior, many retailers have looked to geospatial big data analytics when engaging in corporate location planning. Investments in retail locations, and their economic importance in an increasingly evolving and changing marketplace, have brought significant pressures on decision-makers to adopt more data-driven decision-making practices. With increased intricacies around consumer behaviours, resulting from significant growth in e-commerce and omni-channel integration, many retailers are finding it increasingly important to have more granular level detail about consumer behaviours as the demand and need for retail spaces are changing. By generating better consumer insights, retailers hope to improve their understanding of how, where, when and why consumers shop.

There have been a number of studies focusing on retail location decision-making practices [1, 2, 3, 4, 5, 6, 7, 8, 9, 10, 11, 12, 13, 14, 15]. Specifically, the research domain has focused on data visualization (e.g., customer mapping), site selection, sales forecasting, trade area analysis and, more broadly, location portfolio management. With constant change and evolution in the development of new technologies, data sources and methodologies, there is a need to update our understanding of the role that geospatial big data plays in RLDM. As a result, this study examines the current state and progress in: (1) the type and scale of location decisions that retail firms undertake; and, (2) the availability and use of geospatial and analytics within the decision-making process.

2. Research context

2.1 History of corporate location planning

Before the 1980s, RLDM methods relied heavily on the experience and institutional knowledge held by the decision-maker [16, 17]. In the 1980s and 1990s, RLDM underwent a significant change as it moved towards greater sophistication, resulting from the growth in information technologies, most notably, Geographic Information Systems (GIS). The growth in GIS resulted in a greater prioritization of understanding geographic markets, consumer behaviour and competition [13, 14]. Subsequently, this acted as a catalyst for increasing the availability of data, such as point of sale data, consumer survey data, competitor data, and census data (demographic and socio-economic information) [9, 6, 11, 12]. Capabilities to map store and consumer locations, along with the ability to import demographic and socio-economic datasets to profile customers, allowed for increased reliance on data-driven decision-making [18]. Since its inception, GIS has been a commonly used tool in RLDM for trade area analysis and network planning initiatives [19, 11, 20, 14].

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The last two decades have largely been defined by the increased sophistication in both data collection and data mining techniques able to identify patterns in consumer behaviours. Geospatial big data has been given a significant amount of attention as it is seen to be altering research processes and the way retail professionals engage with data while making decisions [21, 22, 23]. With the exponential growth in the amount of data being collected by retail practitioners, it is important to investigate the way that these data sources are being integrated into the traditional methodologies and technologies that have dominated the RLDM processes since the 1980s and 1990s, as well as, how and if this new data is resulting in new data mining approaches. With data storage and data mining obstacles being less prevalent as a result of technological advancements (e.g., cloud computing and analytics) [13, 14, 24], it is becoming easier to collect, organize and use big data (non-spatial and spatial).

A major area of research and industry attention has focused on the use of modern tracking technologies, as these are seen to provide new opportunities to examine the effects of individual travel patterns on human behaviour, ultimately allowing for a better understanding of individuals and their movements (e.g., space-time prisms, space-time paths, and potential path areas (PPA)). The advancements in spatial big data and associated analytics have allowed for more granular level human behaviour data to be collected. Specifically, the widespread integration of Geographic Positioning System (GPS) within mobile devices (e.g., smartphones) has resulted in significant growth in the collection and analysis of spatial-temporal data [28]. With GPS-enabled devices becoming cheaper and more portable, it is becoming easier to track individual travel patterns. Many companies now compile, clean and sell smartphone location data and associated analytics services, making such data a more readily available resource that is leveraged within private and public sector decision-making applications.

The last Canadian study that investigated the use of geospatial big data and analytics by different retail sectors was by Aversa et al. 2018 [14]. Their study highlighted significant changes in the data environments found within retail firms, as the majority of respondents (well over 80%) indicated overwhelming increases in the variety, volume and velocity of data sources. Much of this change in the dimensions and structure of data provided retailers with a greater level of detail on consumer behaviours. Data collected through sensory-based technologies (RFID) and indoor position systems (IPS) were seen to be major advancements within RLDM. When looking at RLDM techniques, Aversa et al. (2018) reported that only one-third of the survey respondents indicated some use of advanced big data techniques and methodologies such as machine learning, social media analytics, social influence analysis, sentiment analysis, and real-time data/demand visualization. Their study also identified that a number of aspects of location decision-making remain unchanged as retail decision-makers still relied heavily on traditional data sources (census data, population projection and estimate data), and own store data (e.g., store sales, customer counts) and established RLDM methods such as experience, checklists, analogue, and multiple regression techniques. With more than five years since the last major RLDM study, there is a need to identify if geospatial big data and analytics are starting to garner more traction in the way that retail practitioners make decisions.

3. Method

This study surveyed retail sector professionals who are responsible for making location decisions within major Canadian retail and service firms. The survey consisted of closed-ended questions, including rating scales, and forced choices. The questions covered four central themes: (1) personal questions aimed at identifying the respondents and their level of experience; (2) data usage and availability questions designed to audit the businesses data environment; (3) decision-making techniques and methods questions, to identify the range of decision support tools used; and, (4) business culture questions, aimed at providing organizational context for the decision-making activities the business undertakes. For comparative purposes, a number of questions were adopted from Aversa et al. (2018), Hernandez and Emmons (2012) and Byron et al. (2001) [14, 25, 26]. This was needed to evaluate both the current state as well as the degree of change experienced in corporate location planning over time. Supplementary questions were also included in order to capture changes in the data, methods and techniques available to contemporary retail location decision-makers.

3.1 Sample population

The online survey was circulated via personalized emails to 250 professionals that were identified as being responsible for corporate location planning. It should be noted that undertaking organizational research within the retail and service sector can be challenging due to the underlying structure of the industry. In Canada, there is significant corporate concentration in the retail sector, with the three largest retailers in Canada accounting for 25 percent of all non-automotive retail sales [27]. As a result of this concentration, a purposive sampling technique was used to identify relevant respondents within the relatively small number of organizations that account for the largest amount of retail sales within the industry. The contact information for the potential respondents was gathered via industry networks through the Centre for the Study of Commercial Activity (CSCA), the International Council of Shopping Centres (ICSC), company websites and LinkedIn. The participation email outlined the purpose of the study and offered a complimentary summary report of the survey's findings to respondents. All responses are reported in aggregated form to maintain anonymity.

4. Results

A total of sixty-four individuals participated in the survey, representing a 25.6 percent overall response rate. Table 1 illustrates a breakdown of these participants by three broad sector groupings: retail, food services, and other. Retail included any retail firm that belonged to the nine major retail categories (general merchandise, grocery, clothing and clothing accessories, home improvement, home furnishing, electronics and appliances, health and personal care, miscellaneous stores and hobby stores). Food services include restaurants and fast-food chains (often found in retail environments, e.g., shopping centres). The other category included retail services such as banking, developers, leasing and brokerage firms, and retail consultants. The questions in the survey were not all mandatory. Sample sizes (*n*) by question varied and are indicated in tabular results.

Table 1: Response Rate by Sector

Sector	Sample	Respondents	Response Rate (%)
Retail	126	26	20.6
Food Service	54	18	33.3
Other	70	20	28.6
Total	*250*	*64*	*25.6*

Most respondents operated large store networks, with more than 75% of the respondents indicating that their organization operated more than 100 locations (Table 2**)**. While there were respondents with varying levels of industry experience, the vast majority worked in the field for over 11 years (Table 3). Furthermore, the respondents held a variety of positions, with Senior Managers and Managers accounting for just over 67% of all respondents (Table 4).

Table 2: Store Network Size

No. of Stores	% of Total
<10	6.7
10-30	6.7
31-60	1.7
61-100	8.3
101-250	11.7
251+	65.0
Total	*100.0*

Table 3: Timeframe Employed by Current Employer and within Retail Field

Timeframe	% of Total Respondents with Current Employer	% of Total Respondents within Retail Field
Less than one year	14.3	3.1
1 year - 2 years	7.9	3.1
3 - 5 years	23.8	6.3
6 - 10 years	17.5	15.6
11 - 20 years	20.6	42.2
20+ years	15.8	29.7
Total	*100.0*	*100.0*

Table 4: Job Position

Position	% of Total
Owner/Executive/C-Level	21.9
Senior Management	37.5
Manager	29.7
Analyst	6.3
Other	4.7
Total	*100.0*

While the respondents had a variety of responsibilities, the most common responsibilities included new store development of established formats (82.4 percent), management of the existing portfolio through refurbishment (71.2 percent) and the management of the existing portfolio through extensions (64.7 percent) (Table 5).

Table 5: Location-Decision Making Responsibilities *(n=52)*

Decision Type	Always	Often	Sometimes	Rarely	Never
Acquisition of groups of retail properties	5.9%	7.8%	23.5%	31.4%	31.4%
Acquisition of operating divisions	2.0%	4.0%	6.0%	32.0%	56.0%
Acquisition of individual retail properties	30.0%	28.0%	14.0%	20.0%	8.0%
New store development of established formats	45.1%	37.3%	15.7%	2.0%	0.0%
New retail property development of new formats	29.4%	29.4%	25.5%	15.7%	0.0%
Disposal of individual retail properties	21.2%	17.3%	26.9%	26.9%	7.7%
Disposal of groups of retail properties	11.7%	3.9%	9.8%	27.5%	47.1%
Disposal of operating divisions	7.8%	0.0%	9.8%	17.7%	64.7%
Management of existing portfolio through refurbishment	38.5%	32.7%	15.4%	9.6%	3.9%
Management of existing portfolio through relocations	28.9%	26.9%	30.8%	9.6%	3.9%
Management of existing portfolio through re-fascias / re-bannering	19.6%	13.7%	31.4%	15.7%	19.6%
Management of existing portfolio through extensions	35.3%	29.4%	13.7%	11.8%	9.8%

4.1 Data usage

Respondents were asked a variety of questions aimed at identifying whether there have been changes to their organization's data environments in the past few years. Firstly, the respondents were asked how their data has changed based on the traditional 3V's associated with big data (Velocity, Variety, and Volume). Respondents indicated moderate to significant increases in data volume (93.9 percent), data variety (93.8 percent) and data velocity (85.7 percent) (Table 6). The widespread increase in data across the 3V's highlights the potential scale of the opportunities and challenges faced by organizations.

Table 6: Big Data Changes in Past Few Years *(n=49)*

	Significant Increase	Moderate Increase	No Increase
Data Volume	61.2%	32.7%	6.1%
Data Variety	57.1%	36.7%	6.1%
Data Velocity	46.9%	38.8%	14.3%

The respondents identified a wide range of data sources frequently collected or acquired for corporate location planning (Table 7). Census data, population, projected data, and own store location data were the most used data sources (91.8 percent, 91.8 percent, and 91.7 percent, respectively). Daytime population data (80.9 percent), competitor location data (87.5 percent) and consumer expenditure data (78.7 percent) were utilized frequently by well over three-quarters of all respondents. The least frequently used data sources were customer flow/footfall data generated from internal tracking technologies (Local Beacons, RFID or Door Counters) (21.3 percent), customer after-sales data (25.0 percent) and mobile data generated from company-based mobile applications (25.5 percent) with approximately only a quarter of respondents indicating that they used these data sources frequently. Notably, approximately three-fifths of the respondents indicated using mobile data from third-party providers (59.6 percent).

Table 7: Frequently Used Data Sources *(n=49)*

Type of Data	Always	Often	Sometime	Rarely	Never
Customer Transaction Data (e.g., EPOS)	51.0%	22.5%	18.4%	6.1%	2.0%
Customer After-Sales Data (e.g., warranty)	14.6%	10.4%	14.6%	20.8%	39.6%
Customer Survey Data (e.g., exit intercepts)	31.3%	14.6%	20.8%	22.9%	10.4%
Store Card Data (e.g., loyalty programs)	35.4%	25.0%	14.6%	8.3%	16.7%
Credit Card Data (e.g., VISA, Mastercard, Amex)	19.2%	12.8%	21.3%	19.2%	27.7%
Own Store Location Data (e.g., store size, store type, merchandise mix)	79.2%	12.5%	4.2%	4.2%	0.0%
Competitor Location Data	62.5%	25.0%	10.4%	2.1%	0.0%

Planning Application Data	25.5%	21.3%	36.2%	8.5%	8.5%
Social Media Data	12.8%	21.3%	23.4%	29.8%	12.8%
Website Tracking Data	14.9%	17.0%	29.8%	21.3%	17.0%
Census Data (Demographic and Socio-Economic)	71.4%	20.4%	8.2%	0.0%	0.0%
Population Projection and Estimate Data	67.4%	24.5%	8.2%	0.0%	0.0%
Daytime Population Data	53.2%	27.7%	14.9%	2.1%	2.1%
Consumer Expenditure Data	51.1%	27.7%	10.6%	4.3%	6.4%
Consumer Wealth and Financial Data	47.8%	23.9%	17.4%	6.5%	4.4%
Geodemographic/Psychographic Segmentation Data	40.4%	19.2%	14.9%	14.9%	10.6%
External Mobile Data from Third-Party Provider/s	40.4%	19.2%	10.6%	10.6%	19.2%
Internal Mobile Data from own Company App	19.2%	6.4%	21.3%	17.0%	36.2%
Customer Flow/Footfall Data from Local Beacons, RFID or Door Counters	10.6%	10.6%	27.7%	17.0%	34.0%

4.2 Methodologies, technologies and corporate culture

To understand how data are used, current locational decision-making practices were explored in detail. Respondents indicated that trade area identification (95.9 percent), site screening (94.0 percent), sales forecasting (94.0 percent), competitor analysis (88.0 percent) and network optimization (75.5 percent) were operationalized most frequently (Table 8). These were likely most common because they work well with established GIS technologies. In order to investigate the relative use of traditional and more novel decision-making techniques, respondents were asked how frequently they engage in various corporate location planning techniques (Table 9). More novel forms of corporate location planning techniques such as artificial intelligence, machine learning, social media analytics, real-time demand forecasting, and customer sentiment analysis are the least utilized techniques in corporate location planning. The least utilized application was social media/influencer analytics, with 63.8 percent of the respondents indicating rarely or never using this location application. Analyst experience proved to be the most utilized technique for corporate location planners when making decisions, with 95.2 percent of the respondents indicating frequent use. This was followed by analogues-based approaches (91.8 percent) and the checklist method (85.4 percent).

Table 8: Locations Applications Used by the Department/Unit (*n=50*)

Type of Application	Always	Often	Sometimes	Rarely	Never
Trade area identification	85.7%	10.2%	0.0%	2.0%	2.0%
Mobile data analytics and mapping	59.2%	10.2%	12.2%	8.2%	10.2%
Site screening and selection	82.0%	12.0%	6.0%	0.0%	0.0%
Sales forecasting/performance	78.0%	16.0%	0.0%	2.0%	4.0%
Network optimization	57.1%	18.4%	12.2%	4.1%	8.2%
Media analysis/buying	8.2%	4.1%	14.3%	34.7%	38.8%
Logistics/supply chain planning	12.2%	16.3%	16.3%	18.4%	36.7%
Competitor analysis	58.0%	30.0%	10.0%	0.0%	2.0%
Customer profiling and targeting	51.0%	20.4%	16.3%	6.1%	6.1%
Store portfolio segmentation	40.8%	26.5%	22.5%	2.0%	8.2%
Tenant/Merchandising mix analysis	24.5%	22.5%	18.4%	10.2%	24.5%

Table 9: Decision-making Techniques Used (*n=49*)

Technique	Always	Often	Sometimes	Rarely	Never
Experience	69.4%	26.5%	4.1%	0.0%	0.0%
Checklists (e.g. scoring and ranking locations)	47.9%	37.5%	6.3%	4.2%	4.2%
Analogues (store to store comparisons)	63.3%	28.6%	8.1%	0.0%	0.0%
Data Visualization (e.g. data dashboards, live visual analytics)	49.0%	26.5%	18.4%	4.1%	2.0%
Cluster Analysis	25.5%	27.7%	21.3%	14.9%	10.6%
Multiple Regression	23.9%	26.1%	15.2%	15.2%	19.6%
Gravity Models/Spatial Interaction	14.9%	29.8%	8.5%	19.2%	27.7%
AI/Machine Learning	17.0%	8.5%	27.7%	12.8%	34.0%
Real-Time Demand Forecasts	17.0%	8.5%	25.5%	25.5%	23.4%
Customer Sentiment Analysis (e.g., customer feedback, product or service reviews)	26.1%	19.6%	17.4%	30.4%	6.5%
Social Media/Influencer Analytics	10.6%	10.6%	14.9%	40.4%	23.4%

In order to gauge corporate views around geospatial big data adoption, the respondents were asked a series of attitudinal questions. It was evident that corporate location planning initiatives are largely oriented toward data-driven decision-making, with 87 percent of the respondents either strongly agreeing or agreeing with this statement. Furthermore, 91 percent of all respondents indicated that their decision-making efforts are driven by metrics, and 85 percent indicated that corporate location decisions are based on detailed analysis and research (Table 10). Also important to note is that two-thirds of all respondents indicated that their business units view geographic data as a vital part of their decision-making process. The most significant challenges to adopting more data-driven decision-making stemmed from the inability of the organization to both measure and handle data (Table 11). With more sophisticated and complex data sources, the use of data visualization to communicate complex insights in order to make faster retail location decisions was identified as a concern by 20.5% of all respondents. Organizations indicated that acquiring talent with the right set of skills proved to be an area of concern (57 percent). Furthermore, the respondents also indicated challenges in spreading and sharing best practices across their organization (Table 12).

Table 10: Corporate Culture and Data-driven Decision-making (*n=47*)

Statements	Strongly Agree	Agree	Neither Agree or Disagree	Disagree	Strongly Disagree
Our company is oriented towards decisions that are supported by data analytics	61.7%	25.5%	8.5%	4.3%	0.0%
Metrics drive our decision making	53.2%	38.3%	6.4%	2.1%	0.0%
Our company manages our analytics in-house	48.9%	44.7%	4.3%	0.0%	2.1%
The recommendations our department makes are rarely accepted by senior management	2.1%	2.1%	6.4%	44.7%	44.7%
Our company fully leverages 'Geographic Big Data'	23.4%	34.0%	21.3%	19.2%	2.1%
'Geographic Big Data' are a vital part of our department’s decision-making processes	31.9%	36.2%	10.6%	19.2%	2.1%
Analysts understand the techniques they are using	38.3%	48.9%	10.6%	0.0%	2.1%
Our decisions are based on detailed analysis and research	46.8%	38.3%	10.6%	4.3%	0.0%
Multiple techniques are employed for any single decision	51.1%	36.2%	10.6%	2.1%	0.0%
Experience is the most important factor when making decisions in the retail industry	10.6%	46.8%	31.9%	8.5%	2.1%

Model accuracy is let down by inaccurate source data	21.3%	31.9%	34.0%	12.8%	0.0%
We often do not have the time to undertake in-depth analysis	2.1%	29.8%	25.5%	27.7%	14.9%
Our Senior Management fully buy-in to big data analytics	38.3%	29.8%	17.0%	14.9%	0.0%
Management support data driven decision making	51.1%	34.0%	12.8%	2.1%	0.0%
Big Data is viewed as a corporate resource	34.0%	29.8%	21.3%	14.9%	0.0%
Data resources are tightly controlled in department silos	2.1%	27.7%	40.4%	23.4%	6.4%

Table 11: Difficulties with Data Integration *(n = 44).*

Data Capabilities	**Excellent**	**Good**	**Poor**	**Very Poor**
Acquiring data	34.1%	52.3%	13.6%	0.0%
Ability to handle and manage data	38.6%	43.2%	18.2%	0.0%
Acquiring talent	18.2%	72.7%	9.1%	0.0%
Senior management involvement in data analytics activities	27.3%	59.1%	11.4%	2.3%
Securing funding to support data analytics	34.1%	47.7%	18.2%	0.0%
Tracking success of data initiatives	20.5%	59.1%	18.2%	2.3%
Creating flexibility in existing processes to leverage new data sources	22.7%	61.4%	15.9%	0.0%
Finding and deploying the right data technologies	20.5%	63.6%	15.9%	0.0%
Understanding how to use data analytics for business improvement purposes	34.1%	54.6%	11.4%	0.0%
Data visualization in order to communicate complex insights so that the decision-making process can move quicker	27.3%	52.3%	20.5%	0.0%
Leveraging the geography in your data sources	29.6%	56.9%	13.6%	0.0%

Table 12: Organizational and Human Resource Dimensions *(n=43)*

Statements	**Strongly Agree**	**Agree**	**Neither Agree nor Disagree**	**Disagree**	**Strongly Disagree**
The procedure for location decision-making is codified in a training manual (i.e., documented)	4.6%	16.3%	30.2%	37.2%	11.6%
New analysts in our team learn by doing	16.3%	67.4%	16.3%	0.0%	0.0%
Analysts have regular meetings to discuss new findings and learnings	23.3%	51.2%	20.9%	4.7%	0.0%
Analysts are encouraged to attend location planning-related events to benefit from externally sourced knowledge and insight (e.g., relevant conferences, etc.).	18.6%	48.9%	20.9%	11.6%	0.0%
Analyst experience is a fundamental resource within our department.	16.7%	45.2%	26.2%	11.9%	0.0%
Senior analysts act as mentors to new staff	44.2%	39.5%	9.3%	7.0%	0.0%
It is difficult finding new staff with the right mix of skills	11.6%	46.5%	34.9%	7.0%	0.0%
We could spread best practice more effectively	11.6%	55.8%	27.9%	4.7%	0.0%
Our department is good at ensuring that the knowledge of employees who leave is not lost to the organization	9.3%	41.9%	32.6%	14.0%	2.3%

5. Discussion and conclusion

When comparing the results of this survey to previous surveys, several similarities and differences exist around the way the RLDM takes place. Firstly, when compared to Aversa et al., 2018, it is clear that there has been very little change in regard to the heavy reliance that retail practitioners have on traditional data sources [14]. Both surveys indicated that the most frequently utilized data sources were census data, population projected data, competitor location data and own store data. With that said, retailers' attempts to gain greater access to more granular-level customer data proved to be significant data-oriented advancements since the Aversa et al., 2018 study. Developments in sensory-based technology, traffic data, store space planning data, and daytime population data are starting to increase the breadth of customer data that retailers have access to. With the adoption of new technologies, such as the Indoor Position System (IPS) and External Mobile Data from Third-Party Providers, there is the potential for greater detailed tracking of both consumers and potential consumers. When compared to Aversa et al., 2018, the most notable difference exists around the use of customer tracking data (mobile data purchased from third-party providers), as more than half of all respondents (59 percent) indicated frequent use of this data for RLDM, whereas previous results indicated these data sources being used by less than 15% of all respondents [14]. This is not surprising as there has been major growth in the number of companies that sell app-generated smartphone data.

The range of location research methods that are employed within retail firms has also gone through some significant changes. New emerging techniques are continuing to alter the ways that retail location decisions are made. With more than a quarter of the respondents indicating frequent use of advanced forecasting techniques (*e.g.,* artificial intelligence, machine learning, social media analytics, real-time demand forecasting, and customer sentiment), retailers are starting to adopt and assimilate methods that highlight more of the minutia related to consumer behaviour. In 2018, Aversa et al reported these techniques were utilized very infrequently. Most notably is the growth in reliance of machine learning (14.8% vs 25.5%) and social media analytics (3.7% vs 21.2%) [14]. While changes are evident, it is still clear that traditional approaches to RLDM continue to be the most used methodologies. Methods such as experience, checklists, analog, and multiple regression techniques, are still the most predominately used techniques, as was identified in Aversa et al., 2018 [14]. Although there are clearly new sets of techniques available to support RLDM, these techniques are still not widely adopted in Canada.

From these results, it is evident that retail decision environments are continuing to experience significant changes in the collection and usage of geospatial big data, with the bulk of respondents (well over 90%) indicating tremendous growth in the variety and volume of data sources. These changes to the organizational data environments present significant technological opportunities and challenges when attempting to incorporate geospatial big data tools into RLDM. The volume and variety of data now accessible to retail practitioners may well create substantial pressure to overhaul traditional data warehousing as well as the analytical approaches used in decision making. With mobile location data proving to be a key area of growth it is clear that retail organizations are acquiring data that offers a more holistic view of consumer behaviour. With technology redefining consumption behaviours, pressure is clearly growing to better understand how best to serve consumers in a market experiencing significant changes to both how and where consumers buy goods.

With data environments changing quickly, there is a need for more practitioners to be trained with the skillsets required to be proficient in big data environments. With a strong need to be able to communicate the findings from advanced data sources and methodologies (indicated as a significant area of concern for many retail practitioners) there is growing pressure to mobilize the data findings into action as this is proving to be one of the most significant corporate challenges facing the retail sector.

5.1 Limitations and future research

Online surveys are limited in being able to fully capture the complex nature of corporate location planning, there is a need for more research aimed at getting to the minutia of the decision-making process. With big data and analytics being one of the most influential and dominant innovations of the past decade, research focusing on the technical and organizational decision-making challenges with geospatial big data adoption is needed. As a result, this study presents just one part of a multi-dimensional study aimed at untangling the details of how corporate location planning is being affected by big data and analytics. Follow—up semi-structured interviews will be conducted with selected respondents to highlight the nuances that define contemporary RLDM. In-depth interviews will provide further understanding of the factors contributing to the adoption, use and development of big data analytics within RLDM.

6. References

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