ASSESSING USER LOYALTY AND QUALITY OF SERVICE: A VERY DISAGGREGATE APPROACH APPLIED TO PARATRANSIT ARCHIVED DATA

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ABSTRACT

For paratransit operators of small and medium sized communities offering services dedicated to disabled people, it is a challenge to adapt the offered services to the constantly evolving demand while managing the operating costs of an already expensive system and satisfying the users' needs. Archived operational data that describe observed individual travel behaviour are often preserved by paratransit authorities but remain unexploited. This research capitalizes on a totally disaggregate and object oriented approach to develop systematic procedures aiming to extract valuable planning information from this data source. A one-month data sample is used to assess the extent to which individual characteristics of trips and users as well as operational decisions impact the demand for trips and the quality of service. Data mining techniques, linear regression modelling and spatial representations are used. A key finding is that the activity system structures operational decisions. Paradoxically, the way paratransit service is planned can only lead to a reduction of quality of service for loyal users. This paper also illustrates the potential of complete archived operational data to act as a multi-day travel behaviour survey and as a planning tool. To date, operational archived data offer the best available description to assess observed travel behaviour of paratransit users.

Keywords: paratransit, disabled people, operational archived data, observed travel behaviour, multi-day data, totally disaggregate approach, loyalty, quality of service

INTRODUCTION

Travel demand of disabled people is increasing at an exponential rate mainly due to the ageing boom, deinstitutionalization, increase in life expectancy, and a growing desire towards accessibility. For paratransit operators of small and medium sized communities offering services dedicated to disabled people, it is a challenge to adapt the offered services to the constantly evolving demand while managing the operating costs of an already expensive system and satisfying the users' needs... often with limited or no computer-aided software. To characterize demand and operational contexts, rich complete individual operational data are available but still are unexploited due to inexistent systematic procedures.

This research is consequently twofold. First, it capitalizes on a totally disaggregate and object oriented approach to develop systematic procedures enabling the extraction of valuable planning information from the operational archived data. Second, an analytical experiment based on a one-month data sample is conducted to assess the extent to which individual characteristics of trips and users as well as operational decisions impact the demand for trips and the quality of service. Data mining techniques, ordinary least squares (OLS) modelling and spatial representations are used to identify subgroups of users sharing similar consumption patterns and quality of service.

The paper is structured as follows. First, the operational context of paratransit services is presented. A summary of different quality of service indicators found in the literature follows. The potential of large operational archived datasets as a multi-day passive travel behaviour survey is then discussed followed by the proposed research framework and by the dataset characterization. The validation and enrichment process used to assess the loyalty of users as well as the quality of service is then described. At last, the results of the different analysis are presented and discussed, followed by conclusions and future research perspectives.

LITERATURE REVIEW

Paratransit service

Paratransit services are various (vanpools, car sharing, taxis, dial-a-ride, hybrid services, etc.) and no unique definition exists to characterize them. Vuchic (2007) proposed a functional definition based on the offered service and the type of usage:

> "Paratransit is urban transportation service […] provided by private or public operators that is available to certain groups or to the general public, and that is adaptable in its routing and scheduling to individual user's desires in varying degrees".

When the transportation service is exclusively offered to users that can't use regular fixed-route transit services because of disability, age-related conditions or income constraints, paratransit is labelled under the term of Specialized transportation (Ellis & Lynott, 2010).

This study is specifically interested by specialized transportation offered to disabled people. Typically, this service is offered from door-to-door on a demand-responsive basis to patrons who satisfy pre-established criteria (disability type and severity, trip purpose, etc.). Trips usually must be scheduled in advance by the users.

In the province of Quebec (Canada), the passage of a law ensuring the exercise of the rights of people with disabilities in 1978 recognized the responsibility of transit authorities to ensure a public transportation service to disabled people in their respective territory. In 2002, 94.6% of the overall population had access to paratransit service and more than 4.8 million trips were made by more than 62 000 users. Five years later, 98.3% (+3.7%) of the overall population had access to paratransit service and more than 6.4 million trips (+33%) were made by more than 76 000 users (+23%) (Transports Québec, 2007). Such an increase in the quantity of trips, combined with diversification of the clientele and with the complexification of mobility patterns complicate operational decision-making. Nonetheless, just as the regular transit users, they deserve an effective mode of transportation.

Quality of service

The literature extensively describes indicators that can be used to monitor quality of service of demand-responsive and specialized transportation systems (Easter Seals, 2002; Kittelson & Associates Inc. et al., 2003; Chia, 2008). Some of those indicators are resumed in Table 1. Most of the cited references use a qualitative scale to categorize each measure under a finite number of levels of service.

Table 1 – Indicators of quality of service

Measure	Indicator	Source	Description
Availability	Response-time	TCRP100 (Kittelson & Associates Inc. et al., 2003)	Minimum amount of time a user needs for scheduling and accessing a trip or the minimum advance reservation time
	Service span	TCRP100	Number of hours during the day and days per week that DRT service is available in a particular area
Reliability	On-time performance	TCRP100	The degree to which DRT vehicle arrives at the scheduled time
		Project ACTION (Easter Seals, 2002)	
Comfort and Convenience	Trips denied	TCRP100	Trips turned down or denied when requested because of a lack of capacity
		Project ACTION	
	Missed trips	TCRP100	Booked and scheduled trips but are missed because the vehicle does not show up
	Travel time	TCRP100	Comparison between DRT-Auto travel time; Fixed-route-DRT travel time, etc.
		Project ACTION	Too many pick-ups and drop-offs scheduled into group runs Comparison between Fixed-route-DRT travel time

Table 1 – Indicators of quality of service *(continued)*

Measure	Indicator	Source	Description
Efficiency and effectiveness	Serviceability Index (SI)	Sandlin and Anderson (2004)	For rural demand-responsive transit operators based on regional socioeconomic conditions and operational data
User satisfaction	Accessibility index	LaMondia and Bhat (2010)	Based on four individual characteristics: (1) number of minutes the user arrives late at his destination; (2) difference in minutes between scheduled pick-up time and actual pick-up time; (3) difference in minutes between the time spent in the paratransit vehicle and the equivalent time that would be spent in a private vehicle; (4) percent of the users originating from the same zone that were not able to be scheduled during this period

To offer a service that respond to the clients' needs, it is equally important to consider both the operational and the user perspectives when assessing the quality of service of paratransit systems. The clientele of specialized transportation often relies exclusively on this service to satisfy its mobility needs. Individuals with various and frequent out-of-home activities have no other choice but to be loyal to the paratransit system because of their captive status. Nonetheless, loyalty does not systematically ensure a better level of service. Paradoxically, the way service planning is prepared and optimized can often lead to a reduction of quality of service for regular users. To the knowledge of the authors, no research has studied the relationship between the consumption patterns and the quality of service of specialized transportation at the individual level. According to Ellis and Lynott (2010), there is a need to consider more significant individual data to enable evaluation of transportation services "that go beyond counts of trips and miles".

Operational archived data as a travel behaviour survey framework

Many specialized transportation services preserve archived operational databases with individual demographic information on the clientele as well as information on each trip. Traditionally, these operational data are mainly used to assist drivers with their daily routes, to manage revenue or to assess the global performance of the system. Nonetheless, this type of data has the potential to be used as a travel behaviour survey framework and as a planning tool (Menninger-Mayeda et al., 2004; Desharnais & Chapleau, 2010; LaMondia & Bhat, 2010) since it collects information on the trips, the clients and the households. Passive operational archived datasets also have advantages over data collected during standard surveys. They contain precise additional operational information: the exact route and timeline, the driver's ID, and the vehicle number. The sample size is also usually more significant and can even correspond to the complete universe. As for the granularity of the information, it is very disaggregate, being available at the individual level. The data are also available on a multi-day and multi-period scale. Multi-day and multi-period data are better suited than traditional cross-sectional surveys to capture spatiotemporal, inter-personal and intrapersonal variability in activities and trip patterns. Of course, the challenge remains; raw data must be organized, validated and enriched to enable the extraction of valuable information concerning the travel behaviour of the users.

RESEARCH FRAMEWORK

Figure 1 illustrates how a totally disaggregate and object-oriented approach (TDA-OO) can contribute to address this methodological gap. Conceptual and analytical capabilities enabled by the TDA-OO are numerous:

- As an ***integrated informational system [steps 1 and 2]***, the TDA-OO exploits the various relationships existing between the objects of the paratransit system. This allows to link the supply data to additional sources of information associated to the demand (clientele database) and the territory configuration (trip attractor/generator locations). It also preserves all the information of each individual trip: operational information, sequence of movements, purpose, very fine level of spatial resolution (x-y coordinates), temporality, and the socioeconomic attributes of the individual and of the household (Chapleau, 1992).
- As a ***data validation and enrichment process [step 3]***, the TDA-OO assesses the data quality and integrity and ensures a logical and efficient structure of the data. Based on spatiotemporal and ontological logics, initial objects pertaining to the paratransit system are validated and enriched. New attributes and objects are also derived.
- As a ***multi-level-of-resolution framework [step 4]***, the TDA-OO enables the understanding of travel behaviour on a multidimensional scale. Because of the very fine level of spatiotemporal and individual information, various analytical tools and measurement techniques can be employed to assess and derive paratransit consumption and quality of service patterns. Geographic information systems (GIS) are particularly appropriate to link the socio-demographic, spatial, and temporal contexts. In this study, ordinary least squares linear modelling and data mining techniques are also used. Characterization and modelling results enrich the initial datasets.

The following sections of this paper detail each step of the methodological procedure.

DEFINITION OF THE PARATRANSIT SYSTEM

The dataset used in this study comes from a paratransit service located in a medium sized community with a population of approximately 100 000 citizens. The service is offered from door-to-door on a demand-responsive basis to disabled people who satisfy pre-established criteria. The clientele's average age is 56.4 years old and the male-to-female ratio is of 0.726, meaning that more women than men register to the paratransit service. 54.6% of the clientele has a motor disability, 29.6% is intellectually impaired, 10.0% has a psychic disability, and 4.7% is visually disabled. This specialized transportation service is mainly used for leisure, work or study purposes, and to a very less extent, for medical appointments. Schools, hospitals, work places, and activity centres are the locations that generate the most trips. With approximately 250 trips per weekday, this paratransit system is considered as a small paratransit provider. All modes considered, it is more or less one trip out of a thousand that is made using the paratransit transportation system in that region. In terms of public transit trips, the service represents approximately 5% of the annual demand.

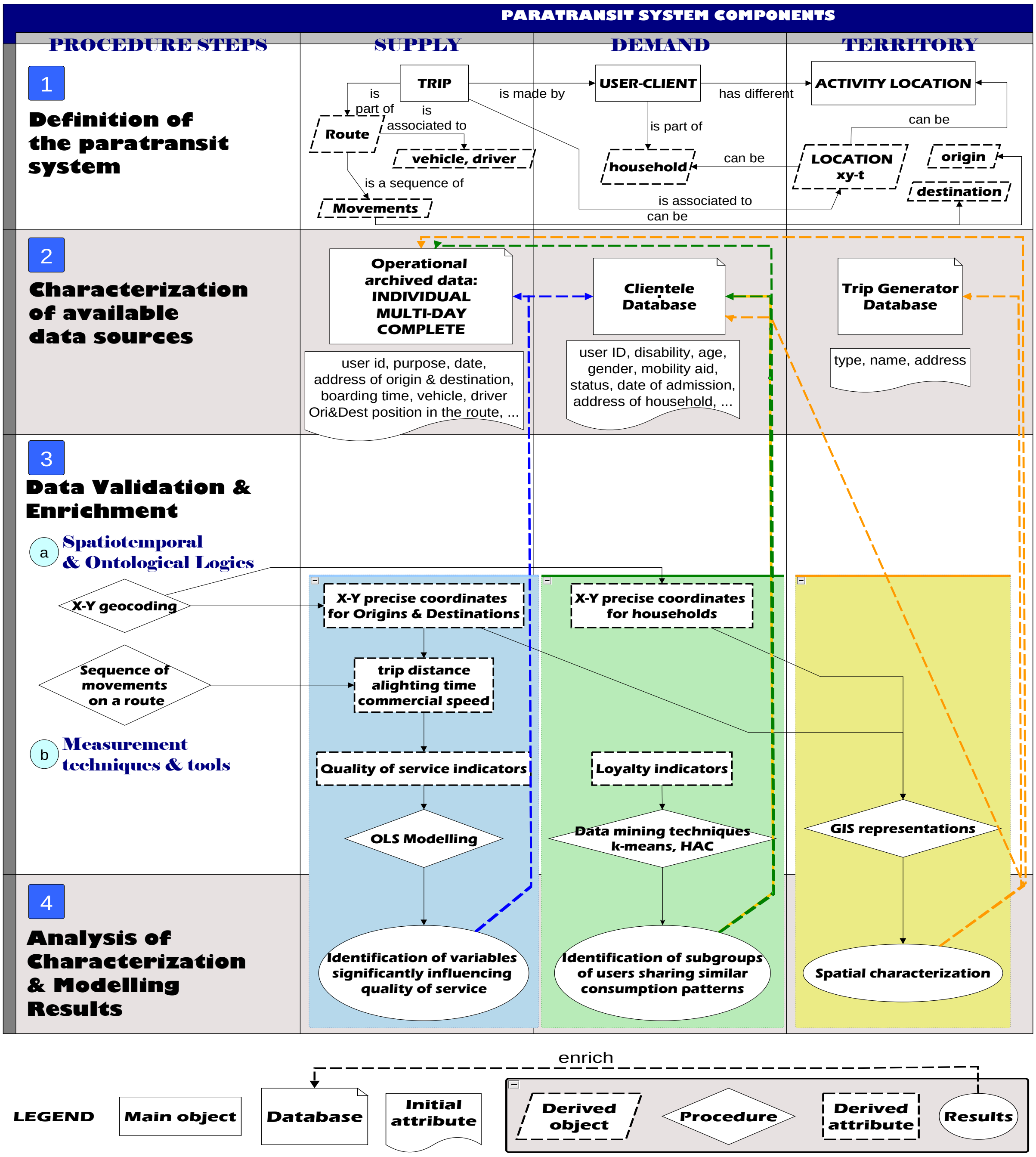


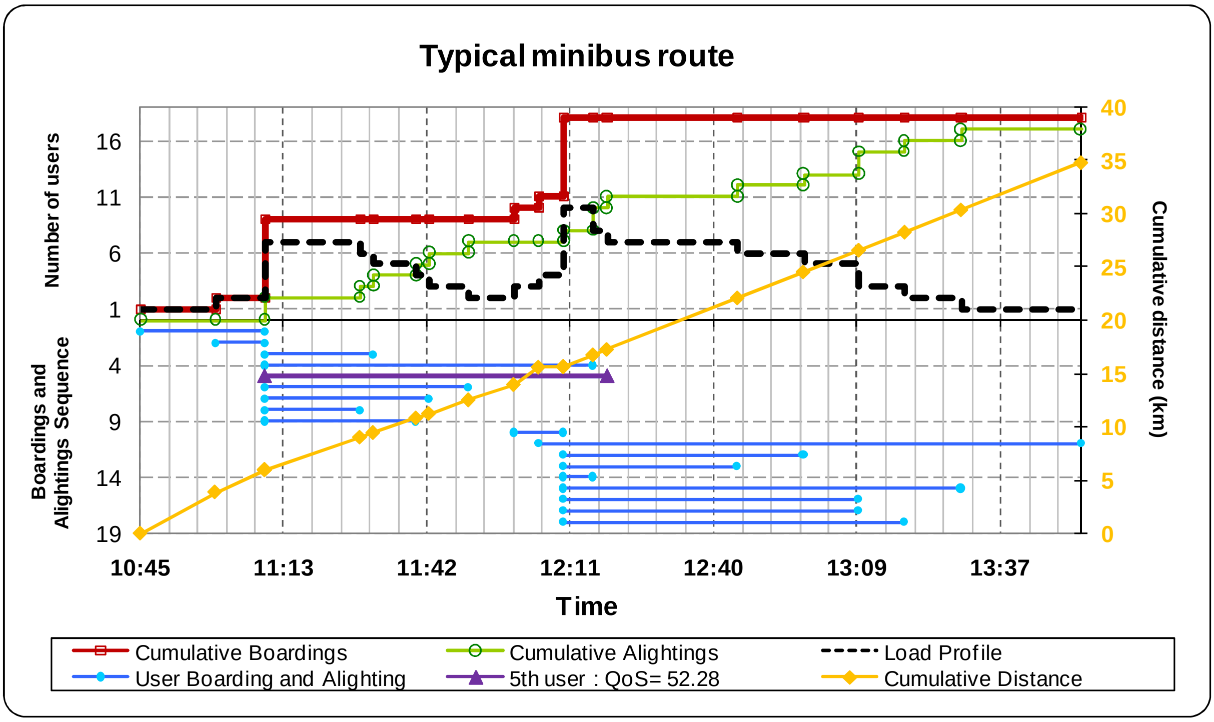
Figure 1 - Research methodological framework

Data collection and structure

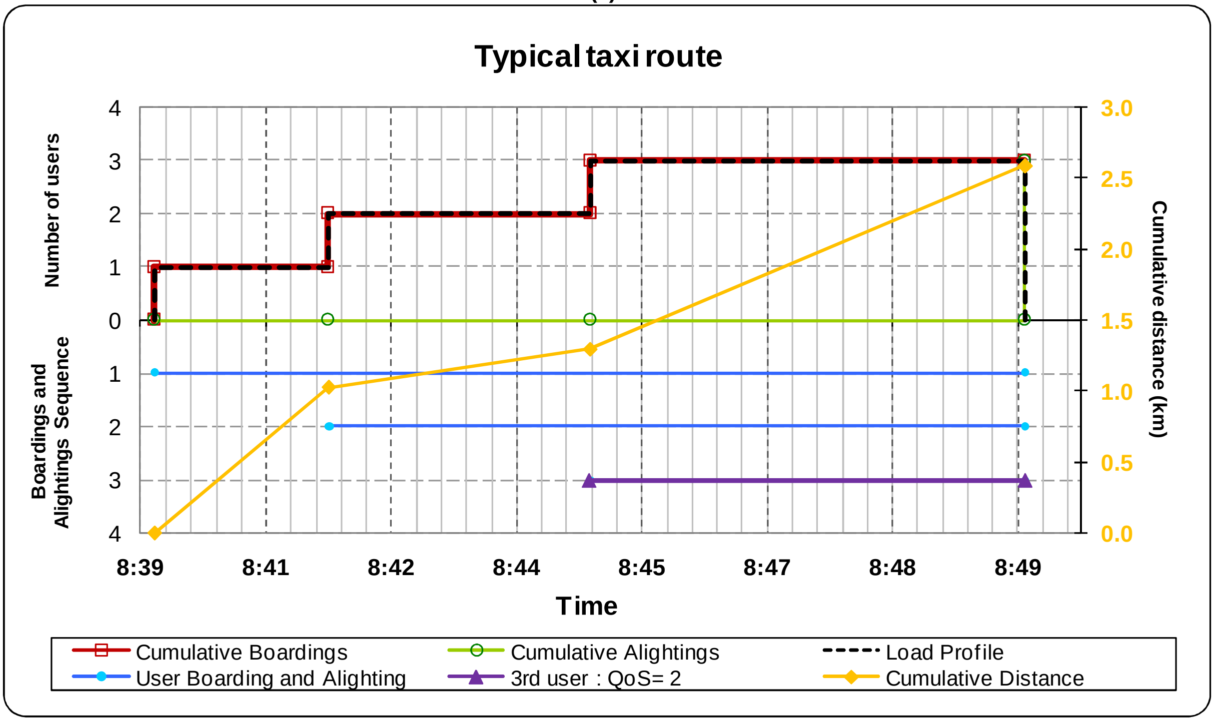
Paratransit operators archive historic data. As illustrated on Figure 1 – Step 2, the main database contains operational information. The main object of this database is the TRIP. Two other databases also hold information: one that provides clientele characteristics on each USER-CLIENT and one that provides information on important trip generators related to ACTIVITY LOCATIONS. From these main objects, other objects can be derived. The schematic representation of the objects structuring the paratransit system (Figure 1 – Step 1) helps understand how the supply, the demand and the territory components interact. A trip is always part of a *route* that is the chronological sequence of *movements* (boarding, alighting) undertaken by the same *vehicle* (minibus, taxi) and *driver*. A route enables the trip of at least one *user*, but is often shared by multiple users that can then be subject to intermediate stops between their *origin* and their *destination* (Desharnais & Chapleau, 2010). Figure 2 presents typical minibus and taxi routes. Routes are daily planned in two consecutive phases. Regular trips with a fixed schedule are the first ones to be assigned. At this stage, operators try to maximize the use of their minibus fleet and minimize the use of private taxi services to reduce operating costs. The operating costs of minibuses are calculated in vehicles-hours. Carrying one or multiple passengers result in the same costs for the paratransit authority. The objective is therefore to group as much users as possible on the same route. Trip constraints (origin and destination location, desired travelling time), operational constraints (availability and capacity of the vehicle) and user constraints (transferability status and type of mobility aid) dictate the optimal groups. Minibuses are usually assigned to long distance trips located in high-density-demand zones. The organization of the activity system facilitates the grouping process, because many regular users share the same time and activity locations and also because many important activity locations are close to each other. By itself, the main destination attracts 20% of all the activities. Consequently, many-origins to few-destinations or few-origins to many-destinations are typical patterns for minibus routes (see Figure 2a). If there is capacity available on one of the minibus routes, occasional trips are added. At last, both regular and occasional trips that could not be assigned to a minibus route are assigned to private taxi services (regular or accessible vehicle). This corresponds to the second planning phase. Conventional taxi routes are composed of short regular trips, occasional long distance trips, or long distance trips located in low-density-demand areas. Few-origins to few-destinations OD is a typical pattern for taxi routes (see Figure 2b).

Dataset

For the purpose of this study, data from two databases are extracted: the trip database and the client database. The valuable attributes for this analysis are: user id; assigned vehicle (minibus, regular taxi or accessible taxi), driver and route; purpose (leisure, medical, work, study or other); address of origin and destination; date; boarding time; code defining the position of the origin and destination on the route. The client database provides socio-demographic characteristics and operational information for each registered individual: ID, gender, age, disability, mobility aid, status (active or not), admission date, and household address. Clients that used the system during the analyzed period are identified by their unique ID in the trip database.



(a)



(b)

Figure 2 – Typical route for (a) minibus vehicle (b) taxi vehicle

Study sample

This specific study is realized using a one-month sample from the archived dataset. One month of data allows the study and identification of distinctive cycles related to weekly consumption patterns. To preserve confidentiality, no denominative information concerning the users is preserved. During the thirty-one-day period, 41% of the registered active clients undertook at least one trip for a total of 5800 trips organized in 1870 routes, each associated with a specific driver and vehicle (minibus, regular taxi or accessible taxi). As for the specific consumption of trips, even if 43.2% of the clientele is over 65 years old, it is responsible for only 14.3% of the trips taken. The same statistic computed for users aged between 20 and 64 years old reveals that they represent 49.1% of the clientele but that they consume 83.4% of the trips.

DATA VALIDATION AND ENRICHMENT

Spatiotemporal and ontological logics

The initial unprocessed dataset consists partly of missing and erroneous information. Data consistency and quality can be validated through spatiotemporal and ontological logics. Spatiotemporal logics verify that space and time constraints are respected. Ontological logics verify that the relations linking the conceptual objects of the paratransit system are respected (refer to Figure 1). An infinite number of spatiotemporal and ontological rules can be derived and tested. In this paper, two validation and enrichment procedures are presented because of their fundamental importance in any successive analysis.

Geocoding of spatial attributes

Precise x-y coordinates are not automatically assigned by the computer-aided system. For each origin, destination and household location, only complete addresses are available in the operational and clientele databases as initial attributes. Based on this information, x-y coordinates can be derived through a web-based automatic algorithm matching the address to its specific spatial location. Poor database quality in the address formats however complicates the geocoding of these spatial data *a posteriori*. In a previous research, Chapleau (2000) lists typical errors encountered when coding approaches are not systematic: spelling mistakes; unique location addressed differently (alias); space suppression; insertion of special characters; affix or road type presence; numerous naming conventions (dashes, numbered streets, etc.). Still, geocoding is an essential enrichment procedure that enables derivation of various meaningful spatiotemporal indicators such as trip distance, speed, or route length (refer to Figure 1 – Step 3a).

Sequence of movements for each route

Once the geocoding procedure is completed, the sequence of movements for each route must be validated. The paratransit authority benefits from a computer-aided system to assist its operators with the data collection process. However, the operators still have to manually assign each user to a vehicle and decide on the sequence of boarding and alighting for each group of users travelling together (on the same route). Any manual operation is highly subject to errors. Manually assigned positions must hence be validated based on available spatial information (x-y coordinates for both origins and destinations) and temporal information (boarding times). If some assigned positions are missing or inconsistent with the spatiotemporal and ontological contexts, they are replaced by the most plausible position on the route. Trip distance, alighting time, number of intermediate stops, and mean commercial speed are all attributes that depend on this validation procedure to be correctly derived afterward (refer to Figure 1 – Step 3a).

Measurement techniques and tools

Specific measurement techniques and tools enrich the initial data by allowing for characterization and modelling of the travel behaviour and operational context. The next sections describe indicators and techniques used to assess both loyalty and quality of service (refer to Figure 1 – Step 3b).

Loyalty indicators

Paratransit operators need to know which users consume what resources, when and where, and with what frequency. Desharnais and Chapleau (2010) have illustrated that subgroups of specialized transportation clientele do not consume trips the same way. Moreover, as Schlich (2001) states:

> "The constraints or obligations may be similar from day to day – but still the chosen activities are not equal. Differences occur because people do not have the same needs every day."

In this paper, travel behaviour variability is observed through the concept of loyalty. Loyalty refers to a combination of frequent use of the paratransit system and the fidelity level associated to a specific spatiotemporal context (destination and day type). Specifically, loyalty is measured as the ratio between:

- the number of days *d*, for a given day type *j*, for which a user *U* utilizes the paratransit service to visit a specific destination *k* (other than his home) and
- the occurrence *D* of day type *j* during the observed period (here one month) *[D_{Monday}=3, $D_{Tuesday}$=4, …, D_{Sunday}=4, $D_{Weekday}$=22, $D_{Weekend}$=8]*

The indicators are computed as described below:

$$L_j^{Uk} = \frac{d_j}{D_j}$$

where L_j^{Uk} is the individual loyalty indicator for a given day type *j* and a given destination *k.*

Note that the second Monday of the observed monthly dataset was not considered in the computation of Monday loyalty indicators, because it corresponds to a Holiday and travel behaviour is not typical. In this paper, the analysis focuses on the day-to-day temporal variability related to individual loyalty. For each client *U,* global loyalty indicators are computed as the sum of the loyalty indicators for all the destinations visited on a given day type *j*.

$$L_j^U = \sum_{k=1}^{n} L_j^{Uk}$$

$$k = 1, 2, \ldots, n$$

Table 2 presents an example of loyalty indicators computation for a given user that visited three different destinations during the observed period. It can be assessed that this user visited the third destination every Monday and Wednesday ($d_{Mon}/D_{Mon}=3/3$; $d_{Wed}/D_{Wed}=5/5$), twice on Tuesdays ($d_{Tue}/D_{Tue}=2/4$), and four Fridays out of five ($d_{Fri}/D_{Fri}=4/5$).

Table 2 – Example of loyalty indicators computation for a user visiting three different destinations during the month

j	Mon	Tue	Wed	Thu	Fri	Sat	Sun	Weekday	Weekend
L_j^{11}	0	0	0	0	0.2	0	0	0.045	0
L_j^{12}	0.33	0.25	0	0	0	0	0	0.045	0
L_j^{13}	1	0.5	1	0	0.8	0	0	0.636	0
$L_j^U = \sum_{k=1}^{3} L_j^{Uk}$	1.33	0.75	1	0	1	0	0	0.727	0

Group characterization by clustering techniques

To identify groups of users that share similar loyalty patterns, clustering techniques are used. A new dataset is created (an example is given at Table 3) that contains a record for each user. Loyalty indicators and number of different destinations visited on each day type *j* during the observed period are the attributes of the dataset.

Clustering analysis is a common statistical technique used to segment observations in different subgroups. This technique allows the maximization of homogeneity within a subgroup and the maximization of heterogeneity between the different subgroups. Others researches have used data mining techniques to characterize variability and similarity in travel behaviour (Morency et al., 2007; Cevallos et al., 2009; Chu & Chapleau, 2010). In this study, the partitioning is done through the application of two successive clustering methods. The k-means algorithm is used to obtain a first partitioning of the data since the computation time of the hierarchical ascendant classification (HAC) algorithm increases very rapidly within large datasets. The number of clusters *k* must be specified as an input. Here, *k* is arbitrarily fixed to twenty groups. Using the twenty-group clusters as an input, a HAC algorithm is then used. This algorithm is appropriate when the number of desired clusters is not known by the expert, because it automatically identifies the optimal number of groups.

Table 3 – Clustering dataset

	Loyalty indicators					Number of visited destinations					
User ID	**LMON**	**LTUE**	**…**	**LWDAY**	**LWEND**	**DMON**	**DTUE**	**…**	**DWDAY**	**DWEND**	**DTOT**
24	1	1	…	1.273	0.25	1	1	…	3	1	4
71	0	0	…	0	0.125	0	0	…	0	1	1

Quality of service indicator

Loyalty indicators characterize the demand. To portray the supply side while still accounting for the user satisfaction towards the service, a quality of service indicator (QoS_i) is built as a generalized cost expressed in minutes. The first term measures the door-to-door difference in kilometres between the paratransit trip distance and the Euclidian trip distance. The second term accounts for the ease of pick-up and drop-off experienced by the user. If at least one other user boards at the same location as user *U*, a fixed penalty of two minutes is added to the QoS indicator. A two minutes penalty is also added if at least one user alights at the same location as user *U*. The third term accounts for the number of intermediate stops experienced by the user between his pick-up location and his drop-off location. For each user *k* that boards or alights at an intermediate stop *j* located between the origin and destination of the user *U* realizing trip *i*, a two minutes penalty is added for a maximum penalty of ten minutes per intermediate stop *j*.

The indicator is expressed as:

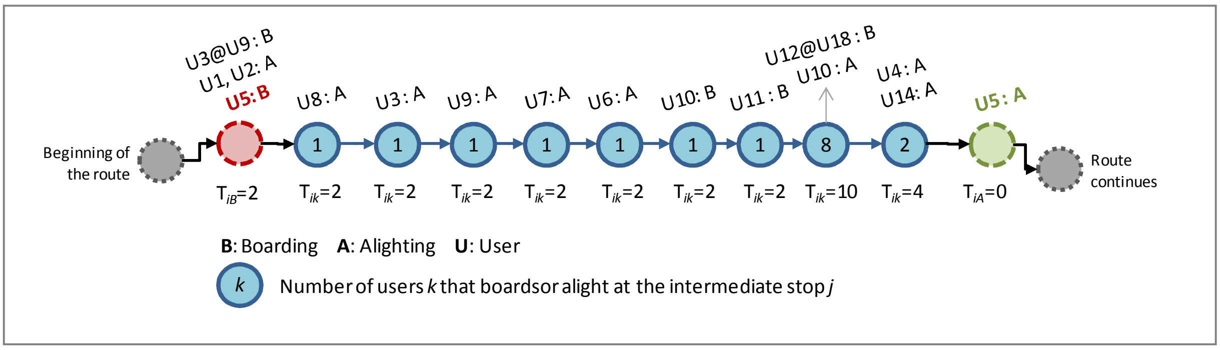
$$QOS_i^U = \left[\frac{(d_2 - d_1)}{s_c} \times 60\right] + [2T_{iB} + 2T_{iA}] + \left[\sum_{j=1}^{m} \left\{\min\left(\sum_{k=1}^{n} 2T_{ik}, 10\right)\right\}\right]$$

where QOS_U^i is the generalized cost of quality of service for trip *i* made by user *U* (in minutes)
d_1 = Euclidian distance from the origin to the destination (km)
d_2 = distance actually travelled by the user *U* from his origin to his destination (km)
s_c = commercial speed (estimated to 15 km/h based on the data)
T_{iB}, T_{iA} = 0 if no other user boards/alights at the same location as the user *U* realizing trip *i* ; 1 in other cases
T_{ik} = 1 for each user *k* that boards or alights at an intermediate stop *j* located between the origin and destination of the user *U* realizing trip *i*
j = 1, 2, ..., *m*
k = 1, 2, …, *n*

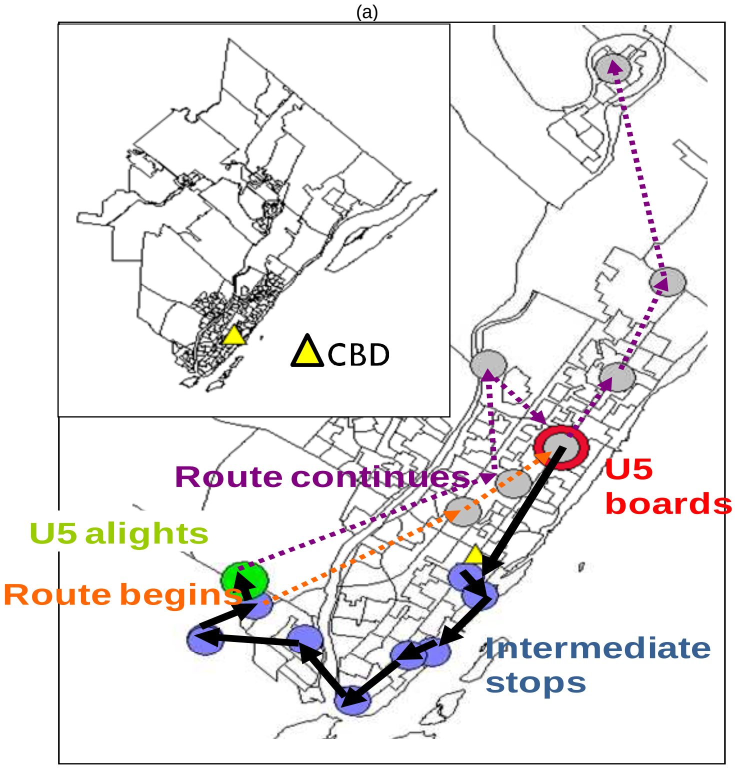
Here follows an example of the quality of service indicator for the fifth minibus trip and the third taxi trip pertaining to the typical routes presented at Figure 2.

Minibus route - trip made by the fifth user:
For the fifth user U5, the chronological sequence of movements is as illustrated on Figure 3. Eight other users board or alight at the boarding location of user U5. Then, user U5 experiences nine intermediate stops with different penalties ranging from two minutes to ten minutes depending on the number of users boarding/alighting at each stop. No other user boards or alights at the alighting location of user U5.

$$QOS_i^U = \left[\frac{(11.46 - 5.89)}{15} \times 60\right] + [1(2) + 0(2)] + [\{7(2) + 1(10) + 1(4)\}] = 52.28$$



(a)



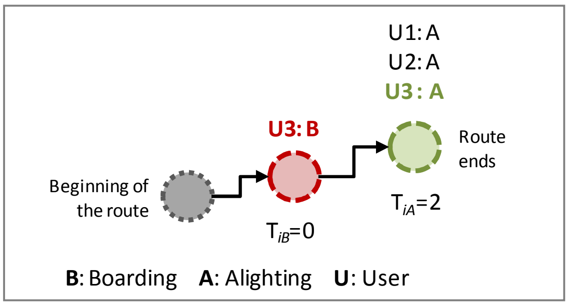
(b)

Figure 3 – (a) Chronological sequence of movements for User 5 pertaining to the minibus route schemed on Figure 2 (b) Spatial representation of the minibus route

Taxi route - trip made by the third user:

For the third user, the chronological sequence of movements is as illustrated on Figure 4. No other user boards or alights at the boarding location of user U3. User U3 experiences no intermediate stops. Two other users alight at the alighting location of user U3.

$$QOS_i^U = [0] + [0(2) + 1(2)] + [0] = 2$$



(a)

(b)

Figure 4 – (a) Chronological sequence of movements for User 3 pertaining to the taxi route schemed on Figure 2
(b) Spatial representation of the taxi route

It can be observed that a better quality of service results in a lower indicator. A zero value means that the user travels alone and experiences the best quality of service.

Linear regression modelling

To examine how loyalty and other attributes affect quality of service, two ordinary least squares linear models are implemented. One evaluates the average quality of service for each user and the other assesses the quality of service for each trip. These models can respectively be expressed as:

$$\left(\frac{\sum_{i=1}^{i} QOS_i^U}{i}\right)^{1/2} = \propto + \sum_{j=1}^{m} \gamma_j D_{Uj} + \sum_{k=1}^{n} \beta_k X_{Uk} + \varepsilon$$

$$\left(QOS_i^U\right)^{1/2} = \propto + \sum_{j=1}^{m} \gamma_j D_{ij} + \sum_{k=1}^{n} \beta_k X_{ik} + \varepsilon$$

where QOS_i^U = generalized cost of quality of service for trip *i* made by user *U* (in minutes)
α = constant
D = vector of *m* dummy explanatory variables
X = vector of *n* continuous explanatory variables
γ, β = parameters to be estimated

The first model is weighted based on the total number of trips taken by each user during the analyzed period. For both models, indicators with a value greater or equal to a hundred were not considered since they were introducing too much bias. Table 4 details the variables included in the models. Results are presented in the next section.

Table 4 – Variables included in the OLS modelling

Model 1 – QoS for each user	
Dummy variable	**Description**
Disability	Type of disability (motor, psychic, visual, intellectual)
Gender	User gender (female, male)
Age cohort	Age cohort (15-75 years old, other)
Household location	Municipality of the household[1]
Loyalty cluster	Loyalty subgroup of user as identified by clustering techniques
Type of client	Type of client (regular, occasional, both)
Continuous variable	**Description**
Number of trips	Number of trips undertaken with respect to vehicle type
Distance travelled	Mean Euclidian distance between origin and destination (km)
Model 2 – QoS for each trip	
Dummy variable	**Description**
Disability	Type of disability (motor, psychic, visual, intellectual)
Gender	User gender (female, male)
Age cohort	Age cohort (15-19, 20-24, …, 60-64, 65-69, other)
Transferability status	Transferability status for the trip undertaken (transferable, non transferable)[2]
Vehicle type	Type of vehicle (minibus, regular taxi, accessible taxi)
Purpose of travel	Purpose of travel (study, medical, work, leisure, other)
Day of travel	Day of travel (Monday, Tuesday, Wednesday, Thursday, Friday, Other)
OD municipalities	Origin-Destination municipality couple
Continuous variable	**Description**
Household location	Euclidian distance between CBD and household location
Boarding time	Boarding time[3]
Destination location	Euclidian distance between CBD and destination location

[1]Municipality locations are identified based on the relative distance between the zone centroid and the CBD location. CBD1 is the closest municipality to the CBD and CBD7 is the more distant. The CBD is defined as the City Hall location.

[2] Not transferable statuses refer to trips for which there are constraints on the vehicle type due to a not foldable wheelchair or to the user incapacity to sit in a normal passenger seat.

[3] The influence of boarding time is measured with noon being the reference. Hence, a trip boarding at noon has a boarding time value of zero. The further the boarding time is from noon, the more the value of the variable grows. The value is rounded-up to the closest absolute integer. For example, a boarding occurring at 9:05 am as a value of (12:00-9:05 = 2:55 = 3) and a boarding occurring at 16:55 as a value of (12:00-16:55 = -4:55 = 5).

RESULTS AND DISCUSSIONS

User loyalty

Clustering results

The HAC algorithm identifies a four cluster solution as the optimal partitioning of the clientele with respect to their loyalty towards the paratransit system. Table 5 presents the size of each cluster. This table already allows an understanding of the partitioning results. Indeed, users of cluster C1 consume much more trips than their relative importance in the overall clientele. Users of cluster C3 also consume more than their clientele share, but the difference is less significant. As for users of cluster C4, they seem to consume very few trips compared to their demographic importance. To further understand what motivated this particular segmentation and determine on which levels each subgroup distinguishes itself from the others, descriptive statistics are presented in Table 6 and Table 7.

Table 6 computes for each cluster: (a) the proportion of users which travelled at least once on a given day type and (b) the mean loyalty on a given day type. The analysis of Table 6 reveals specific temporal trip consumption patterns for each of the cluster groups:

- Cluster C1 is associated with users highly loyal on weekdays;
- Cluster C2 groups users travelling the most on weekend days;
- Cluster C3 is associated with users loyal on weekdays, but less than those in cluster C1, and highly disloyal on weekend days;
- Cluster C4 groups users realizing very few trips during the observed period.

Table 5 - Size of each cluster

CLUSTER	Number of users		Number of trips	
C1	52	18.6%	2506	43.2%
C2	17	6.1%	242	4.2%
C3	69	24.7%	2081	35.9%
C4	141	50.5%	969	16.7%
	279		5798	

Table 6– Subgroup characterization

CLUSTER	MON	TUE	WED	THU	FRI	SAT	SUN	WDAY	WEND
C1	94.2%	86.5%	92.3%	88.5%	98.1%	15.4%	63.5%	100.0%	65.4%
C2	35.3%	47.1%	35.3%	17.6%	41.2%	100.0%	47.1%	82.4%	100.0%
C3	82.6%	79.7%	76.8%	85.5%	71.0%	8.7%	5.8%	100.0%	14.5%
C4	12.1%	27.0%	32.6%	27.7%	39.7%	5.7%	11.3%	94.3%	16.3%

(a) Proportion of users which travelled at least once on a given day type

CLUSTER	LMON	LTUE	LWED	LTHU	LFRI	LSAT	LSUN	LWDAY	LWEND
C1	1.18	1.26	1.34	1.33	1.15	0.41	0.58	1.15	0.33
C2	0.50	0.53	0.50	0.73	0.49	0.74	0.34	0.22	0.45
C3	0.92	0.97	0.94	0.95	0.72	0.29	0.31	0.71	0.15
C4	0.73	0.60	0.48	0.56	0.41	0.25	0.55	0.16	0.23

(b) Mean user loyalty on a given day type

As Figure 1 (Step 4) illustrates, clustering results enrich the initial databases. The distribution of users' sociodemographic characteristics, activities and travel behaviour can also be assessed: within a specific cluster by an intra-group characterization and between the different clusters by an intergroup characterization. Table 7a presents an example of intra-group and intergroup characterizations for one variable (number of travelling days). Table 7b details the complete list of descriptive statistics that were analyzed to characterize the profile of each cluster.

Table 7 – Descriptive statistics computed for each loyalty cluster

CLUSTER	C1	C2	C3	C4
NUMBER OF TRAVELLING DAYS				
1-5	0.0%	29.4%	0.0%	82.3%
6-10	0.0%	41.2%	23.2%	14.9%
11-15	13.5%	29.4%	27.5%	2.1%
16-20	34.6%	0.0%	39.1%	0.0%
21-26	51.9%	0.0%	10.1%	0.7%

Intra-group characterization: one cluster=100%

Intergroup characterization C1 + C2 + C3 + C4 = 100%

CLUSTER	C1	C2	C3	C4	*
NUMBER OF TRAVELLING DAYS					
1-5	0.0%	4.1%	0.0%	95.9%	121
6-10	0.0%	15.9%	36.4%	47.7%	44
11-15	20.6%	14.7%	55.9%	8.8%	34
16-20	40.0%	0.0%	60.0%	0.0%	45
21-26	77.1%	0.0%	20.0%	2.9%	35

* *total number of users*

(a) Example of intra-group and intergroup characterizations for one variable: number of travelling days

Lists of variables used to characterize the profile of each cluster	
User-related	**Description**
Disability	Type of disability (motor, psychic, visual, intellectual)
Gender	User gender (female, male)
Age cohort	Age cohort (14-. 15-19, 20-24, …, 80-84, 85+)
Household location	Municipality of the household (CBD1, CBD2, …, CBD7)
Type of client	Type of client (regular, occasional, both)
Activity-related	**Description**
Different purposes	Number of different purposes (1, 2, 3, 4)
Trips – Study	Number of trips for study purpose (0, 1-10, 11-20, 21-30, 31+)
Trips – Leisure	Number of trips for leisure purpose (0, 1-10, 11-20, 21-30, 31+)
Trips – Medical	Number of trips for medical purpose (0, 1-10, 11-20, 21-30, 31+)
Trips – Work	Number of trips for work purpose (0, 1-10, 11-20, 21-30, 31+)
Trips – Other	Number of trips for other purposes (0, 1-5, 6-10,11-15, 16-20)
Trip-related	**Description**
Travelling days	Number of days for which the client made at least one trip (1-5, 6-10,…, 21-26)
Trips	Number of trips made by the client (1-10, 11-20, …, 61-70, 71-80)
Destinations	Number of destinations visited other than home (1, 2, 3, 4, 5+)
Desire Line	Mean Euclidian length of all trips (in km: 0-2.5, 2.5-5, …, 7.5-10, 10+)
Vehicle type	Type of vehicle used (Minibus, regular taxi, accessible taxi)

(b) Observed variables

Profiles

- *Cluster C1: Users highly loyal on weekdays.* This cluster groups the clients that use the system the most – in terms of number of days and also in terms of number of trips. They are aged mostly between 20 and 54 years old. They are also mostly suffering from an intellectual impairment. Users with an intellectual impairment are often identified in the literature as the group making the most trips (Koffman et al., 2007). As multi-purpose (except for medical trips) and multi-destination travellers, it is not surprising that they use the paratransit system both for regular and occasional trips. When they travel, they are mainly assigned to a minibus vehicle.

- *Cluster C2: Users travelling the most on weekends*. This cluster groups the clients that travel approximately one day out of two. They are occasional users and regular users that use the paratransit system to achieve leisure and medical trips. These types of trip patterns are consistent with the users' age and with their type of disability: users of cluster C2 either pertain to the youngest age cohort (less than 25 years old) or to the oldest age cohort (more than 55 years old). 82.4% are also people with a motor disability. They are also mostly women (76.5%) and 64.7% live in the closest municipality to the CBD. Compared to the relative importance of the cluster in terms of total trips (cluster C2 represents 4.2% of the total trips – refer to Table 5), trips made by accessible taxis are also overrepresented (19.9% of the trips are made using accessible taxi).
- *Cluster C3: Users loyal on weekdays, disloyal on weekends*. They are the second most loyal paratransit users after users of cluster C1. They undertake regular trips, but they have less different purposes and destinations. They are also older than users of cluster C1, being aged mainly between 45 and 64 years old (with peaks of users also aged 20-24 or more than 84). They use the paratransit system to realize different kind of activities, but they don't use it much for medical trips. As users of cluster C1, they are mostly suffering from an intellectual impairment and they travel mostly by minibus. However, as illustrated by Table 6, users of cluster C3 travel less on Fridays and much less on the weekends than users of cluster C1.
- *Cluster C4: Users realizing very few trips*. This cluster groups 50% of the clientele. They are the clients that use the system the less during the whole month with 82.3% travelling five days or less to realize ten trips or less. They can be characterized as "one-dimensional" users since they travel mostly for a unique purpose and towards a unique destination. Compared to the relative importance of the cluster in terms of share of the clientele (50.5% of the users pertains to this cluster – refer to Table 5), occasional users, younger and older users as well as trips associated to long-distance trips (10 km and more) are overrepresented. Trips made by regular and accessible taxis are also overrepresented (24.3% by regular taxi; 44.4% by accessible taxi) compared to the relative importance of the cluster in terms of share of trips (cluster C4 represents 16.7% of the total trips – refer to Table 5).

Quality of service

The following analysis describes the impact of variables that significantly influence the quality of service both at the user-level (Table 8 – Appendix A) and at the trip-level (Table 9 – Appendix B) based on the OLS modelling results. As a reminder, note that higher values for the dependent variable indicate a lower quality of service. Hence, independent variables with a negative sign are positively influencing the quality of service.

Socio-demographic profile - Modelling results

Younger users (less than 15 years old) and older users (more than 74 years old) benefit from the best quality of service (significant at the trip-level). Users aged between 20 and 49 years old are the ones that benefit from the lowest quality of service. As for users aged between

50 to 74 years old or aged 15 to 19 years old, they benefit from an "intermediate" quality of service. Younger and older users are the clients that make the most trips by taxi and the most occasional trip, which explains the increased quality of service.

As for disability types, clients with a motor disability benefit from the best quality of service while users with an intellectual impairment are the most penalized. This is not surprising since intellectually impaired clients are mostly transferable users travelling by minibus for other purposes than medical appointments. All these factors significantly (at the 95% confidence level) contribute to reduce the quality of service of the trip. On the opposite, non transferable users travelling by accessible taxis benefit from an increased quality of service. Trips undertaken for study (significant) or work (not significant at the 95% confidence level) purposes are associated to the lowest quality of service. This is consistent with the fact that study and work are activities usually undertaken by regular loyal users (clusters C1 and C3). As stated before, regular long distance trips, especially if located in high-density-demand areas, are assigned to minibus routes in order to limit operating costs and keep up with the annual budget as much as possible. This increases detours and the number of intermediate stops which reduces the quality of service. As for private taxis, they are mainly assigned to short distance routes. Because they cannot accommodate as much passengers as minibuses, quality of service usually increases.

Figure 5 synthesizes this four-dimensional relation existing between clustering results, user loyalty, quality of service, and user's mean OD desire line for an average weekday. For instance, the left bottom corner of the graph groups users that benefit from a higher quality of service than the average user, but that are not really loyal to the service; the right upper corner of the graph groups users that benefit from a lower quality of service, but that are still loyal to the service. This is consistent with the model results (Table 8 – Appendix A) which indicate that users from cluster C4 are the most advantaged in terms of quality of service and users of clusters C1 and C3, the most penalized. It can also be assessed that users with shorter desire lines (*z* dimension) benefit from a better quality of service.

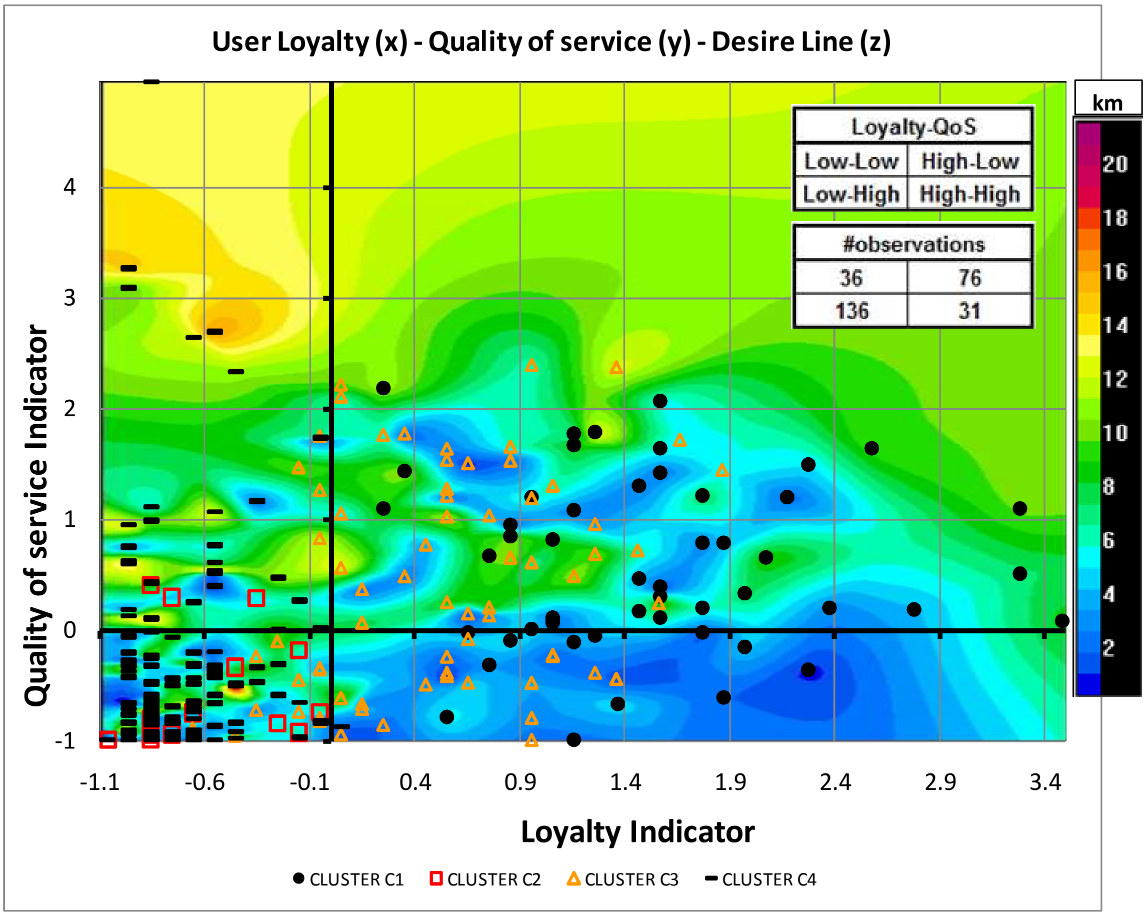


Figure 5 – Four-dimensional relation between clustering results, loyalty, quality of service, and desire line

Note that to facilitate comparisons, loyalty and quality of service indicators were standardized as:

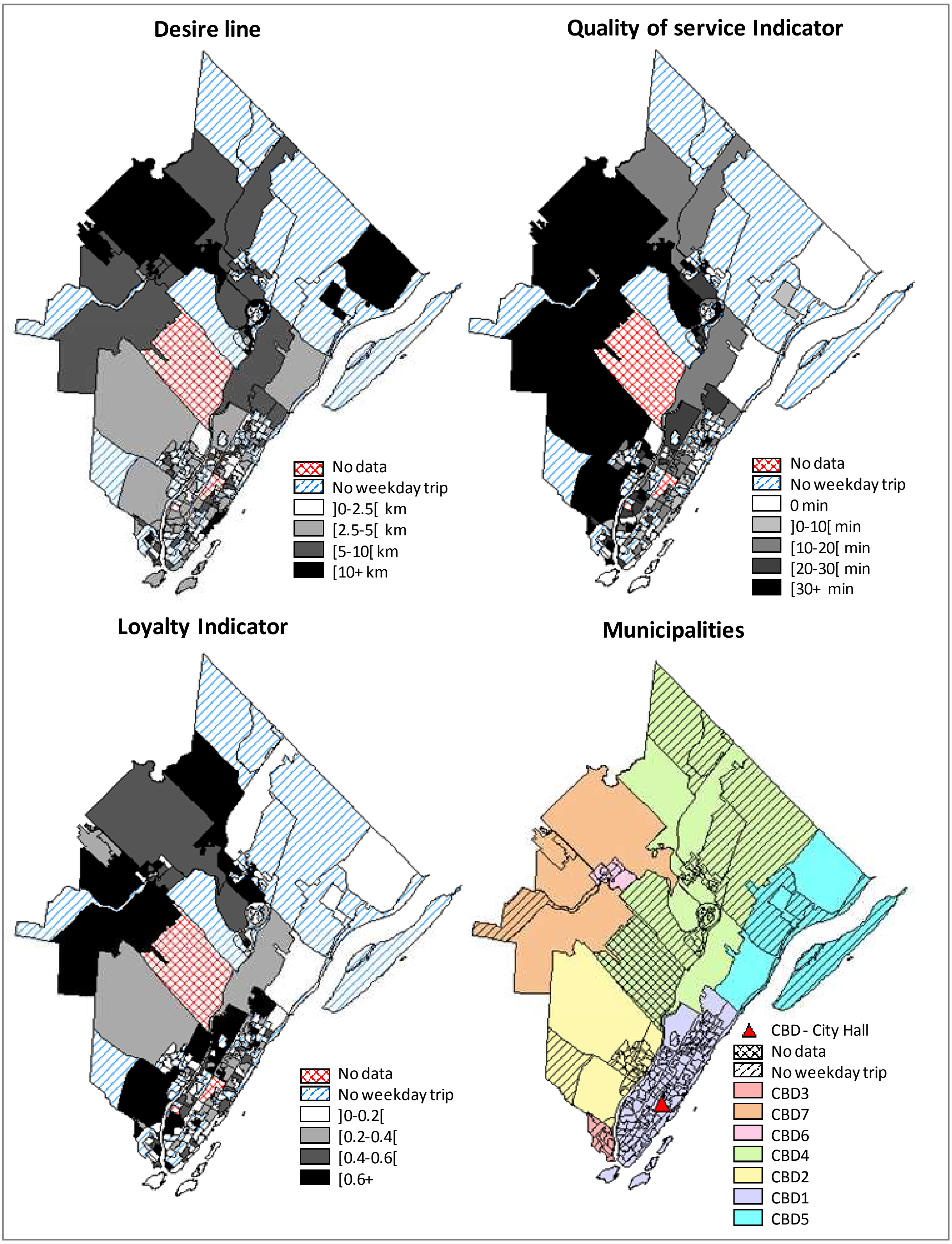
$$L_{weekdays}^{U}{}' = \frac{L_{weekdays}^{U} - \bar{x}}{s}$$

$$QOS_{weekdays}^{U}{}' = \frac{QOS_{weekdays}^{U} - \bar{x}}{s}$$

where $\bar{x}$ is the mean of the indicator and *s* is the standard deviation of the indicator.

Spatiotemporal context - Modelling results

At a time scale level, trips undertaken during mid day benefit from a better quality of service. Indeed, the further the boarding time is from noon, the more the quality of service is reduced. The day of the week on which the trip is made also significantly influences the quality of service. Mondays, Tuesdays and Thursdays are the worst days to take a trip while Wednesday and Fridays are the best. However, according to the data, Saturdays and Sundays are the days where the quality of service is at its best. On Saturdays and Sundays, less people want to travel (only 6.78% of all the trips). There are also more trips made by taxi which means less detours and less intermediate stops and it explains why the quality of service is enhanced compared to weekdays. For this reason, the model is a little biased here. At the spatial level, living closer to the CBD significantly improves quality of service. Figure 6 maps the spatial relationship existing between household location and three indicators: loyalty, quality of service and mean desire line. It can be assessed that users living far from the CBD are more loyal, but need to make longer trips which probably explain the lower quality of service. At the opposite, users living closer to the CBD are using the specialized transportation service less (lower loyalty levels), but when they used it, their trips are shorter which probably explain why they benefit from a better quality of service.



This representation is for weekdays only. The spatial zoning corresponds to the Dissemination Area (DA) which is the smallest standard geographic area for which all Canadian census data are distributed. Approximately 400 to 700 people live in each DA.

Figure 6 – Spatial variability for loyalty, quality of service and desire line

CONCLUSIONS AND FUTURE DIRECTIONS

This paper has examined the associations between user loyalty and quality of service based on socio-demographic attributes of the users, their travel behaviour and operational decisions. The results of the cluster analysis suggest that there are different levels of loyalty according to a given day type and a given socio-demographic profile. As for the modelling analysis, it confirms that quality of service significantly varies depending simultaneously on the characteristics of the user (type of disability, type of client, household location) as well as on the purpose, and the spatiotemporal (OD distance, time of boarding, day of travel, closeness to the CBD) and operational (type of vehicle) contexts of the trip.

Because of the way the quality of service indicator was built and because of the way the service is organized, it was expected that quality of service would be lower for optimized minibus routes. Characterization and modelling results being consistent with the real operational context and the real observed travel behaviour of users confirms the reliability of a systematic methodological framework such as the TDA-OO. This first experiment has succeeded to illustrate that it is possible to use complete archived operational data as a multi-day travel behaviour survey and as a planning tool. To date, operational archived data offer the best available description to assess both the operational context of specialized transportation systems and the observed travel behaviour of its users.

Future research will continue to investigate this new and unique data collection framework. This first step aimed to develop a methodology enabling the extraction of valuable information from historic datasets archived by specialized transportation operators from small and medium sized communities. Service providers need to understand who their clientele is, what the consumption patterns are and how the organisation of the service benefits each client. More work will need to be done to apply this research framework into a practical planning context. In a continuous attempt to optimize the offered services to the observed needs, the next steps will focus on the characterization of the activity system since it plays a key role in both consumption and quality of service patterns. Techniques developed will also be improved by assessing for dynamic changes such as annual variations or seasonal effects on both the loyalty and the quality of service.

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APPENDIX A

Table 8 – Quality of service for each user

R^2		0.730		
$R^2_{adjusted}$		0.709		
s2		2.115		
s		1.45		
n		278		
Weigth variable		Number of trips		
	% of observations	coefficient	*t*-statistic	p value
CONSTANT		3.2825	5.9710	0.0000
DISABILITY				
Motor	41.4	-1.1243	-5.0010	0.0000
Psychic	5.4	-0.2058	-0.7571	0.4497
Visual	4.7	-0.5484	-1.5290	0.1275
Intellectual	48.6		Reference	
GENDER				
Female	59.4	-0.0320	-0.2384	0.8118
Male	40.6		Reference	
AGE COHORT				
15-75	82.0	0.1147	0.3992	0.6901
Other	18.0		Reference	
HOUSEHOLD LOCATION (municipality)				
CBD1	48.6		Reference	
CBD2	15.1	1.4279	7.2880	0.0000
CBD3	9.4	1.4203	6.1120	0.0000
CBD4	15.1	0.8280	3.5490	0.0005
CBD5	1.1	-1.6923	-1.0730	0.2841
CBD6	5.4	1.3636	3.8150	0.0002
CBD7	5.4	2.0490	6.1540	0.0000
LOYALTY CLUSTER				
C1 - Users highly loyal on weekdays	18.7	1.2600	2.8700	0.0045
C2 - Users travelling the most on weekends	6.1		Reference	
C3 - Users loyal on weekdays, disloyal on weekends	24.8	0.8472	2.1810	0.0301
C4 - Users realizing very few trips	50.4	-0.1367	-0.3564	0.7219
TYPE OF CLIENT				
Regular	38.1	-0.0633	-0.4111	0.6813
Occasional	27.3	-1.1004	-3.3010	0.0011
Both	34.5		Reference	
NUMBER OF TRIPS UNDERTAKEN				
Minibus		0.0105	1.3660	0.1730
Accessible taxi		-0.1276	-2.7470	0.0064
Regular Taxi		-0.0616	-6.8290	0.0000
DISTANCE TRAVELLED				
Mean Origin-Destination Euclidian distance (km)		0.1016	3.3670	0.0009

[1] Variables in grey are not significant at the 95% confidence level

APPENDIX B

Table 9 - Quality of service for each trip

R^2		0.495		
$R^2_{adjusted}$		0.489		
s2		3.674		
s		1.92		
n		5765		
	% of observations	**coefficient**	***t*-statistic**	**p value**
CONSTANT		2.8798	10.5700	0.0000
DISABILITY				
Motor	19.8	-1.3443	-14.8100	0.0000
Psychic	6.6	-0.5787	-5.2720	0.0000
Visual	3.8	-0.7898	-5.4280	0.0000
Intellectual	69.8		Reference	
GENDER				
Female	56.4	0.0316	0.5794	0.5623
Male	43.6		Reference	
AGE COHORT				
15-19	2.2	1.1131	3.0600	0.0022
20-24	6.6	1.8044	5.3940	0.0000
25-29	15.0	1.8368	5.6040	0.0000
30-34	10.6	1.7183	5.2460	0.0000
35-39	4.0	2.0218	5.8890	0.0000
40-44	5.9	2.2958	6.8210	0.0000
45-49	15.2	1.8538	5.6510	0.0000
50-54	11.6	1.5858	4.9000	0.0000
55-59	7.8	1.5092	4.4940	0.0000
60-64	5.9	1.4470	4.2720	0.0000
65-69	3.8	1.5385	4.6200	0.0000
Other	3.6		Reference	
TRANSFERABILITY STATUS				
Transferable	93.8	0.5261	4.1110	0.0000
Non transferable	6.2		Reference	
HOUSEHOLD LOCATION				
Distance CBD-Household		-0.0445	-3.944	0.0001
VEHICLE TYPE				
Minibus	66.8		Reference	
Regular Taxi	29.8	-1.8747	-25.1900	0.0000
Accessible Taxi	3.4	-1.4267	-9.2010	0.0000
PURPOSE OF TRAVEL				
Study	28.9	0.2080	2.8400	0.0045
Medical	4.4	-0.7170	-4.5930	0.0000
Work	22.8	0.1210	1.4740	0.1406
Leisure	41.0		Reference	
Other	2.9	-0.6879	-4.2420	0.0000
DAY OF TRAVEL				
Monday	12.2	0.4396	3.3330	0.0009
Tuesday	17.5	0.3457	2.7280	0.0064
Wednesday	22.3	-0.1297	-1.0510	0.2932
Thursday	22.0	0.3283	2.6570	0.0079
Friday	19.2	-0.2511	-1.9730	0.0486
Other	6.8		Reference	
OTHER TRIP CHARACTERISTICS				
Boarding time		0.1059	8.189	0.0000
Distance CBD-Destination		-0.0027	-0.1795	0.8575

[1] Variables in grey are not significant at the 95% confidence level

Table 9 - Quality of service for each trip *(continued)*

	% of observations	coefficient	*t*-statistic	p value
Municipality of Origin and Destination				
CBD1-CBD1	33.7		Reference	
CBD1-CBD2	7.3	1.9220	17.9900	0.0000
CBD1-CBD3	3.9	3.3778	23.8900	0.0000
CBD1-CBD4	6.9	1.3417	7.9620	0.0000
CBD1-CBD5	0.2	-0.7648	-1.1610	0.2456
CBD1-CBD6_7	2.7	3.0311	12.5300	0.0000
CBD1-OTHER	3.1	0.8821	5.0660	0.0000
CBD2-CBD1	7.8	1.9115	18.2400	0.0000
CBD2-CBD2	1.2	0.0288	0.0971	0.9227
CBD2-CBD3	0.2	0.9369	1.6000	0.1097
CBD2-CBD4	0.7	0.8240	2.3860	0.0171
CBD2-CBD5	0.1	2.4256	3.2540	0.0011
CBD2-CBD6_7	0.2	1.1256	1.9250	0.0543
CBD2-OTHER	0.2	3.0734	4.7460	0.0000
CBD3-CBD1	3.8	1.9931	13.9300	0.0000
CBD3-CBD2	0.2	1.3385	2.0670	0.0388
CBD3-CBD3	0.1	0.7682	0.9718	0.3312
CBD3-CBD4	0.1	1.2375	1.5460	0.1222
CBD3-CBD6_7	0.0	-0.3946	-0.2047	0.8378
CBD3-OTHER	1.3	-0.3995	-1.6280	0.1037
CBD4-CBD1	6.3	1.7885	13.6000	0.0000
CBD4-CBD2	0.7	0.6995	2.2260	0.0261
CBD4-CBD3	0.1	0.4609	0.6689	0.5036
CBD4-CBD4	4.7	0.2154	1.0480	0.2946
CBD4-CBD5	0.1	-1.4510	-1.4830	0.1381
CBD4-CBD6_7	1.7	2.1670	7.6590	0.0000
CBD4-OTHER	0.3	2.0122	4.3510	0.0000
CBD5-CBD1	0.1	-0.7915	-0.8165	0.4142
CBD5-CBD2	0.2	3.8638	6.5450	0.0000
CBD5-CBD4	0.1	-1.8759	-1.9200	0.0549
CBD5-OTHER	0.0	2.0736	1.0710	0.2841
CBD6_7-CBD1	3.6	2.2949	12.7200	0.0000
CBD6_7-CBD2	0.2	3.7089	5.9070	0.0000
CBD6_7-CBD3	0.0	-2.7851	-1.4480	0.1477
CBD6_7-CBD4	1.4	2.6844	9.5190	0.0000
CBD6_7-CBD6_7	1.4	0.1917	0.6782	0.4977
CBD6_7-OTHER	0.3	4.2417	8.9880	0.0000
OTHER-CBD1	3.3	1.4892	9.7070	0.0000
OTHER-CBD2	0.1	3.1466	3.9690	0.0001
OTHER-CBD3	1.0	0.5055	1.9310	0.0535
OTHER-CBD4	0.3	2.9898	6.5210	0.0000
OTHER-CBD5	0.0	-1.0838	-0.5596	0.5758
OTHER-CBD6_7	0.3	4.1761	8.0910	0.0000

[1] Variables in grey are not significant at the 95% confidence level

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