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# 1 Exploring the behavior of suburban train users in the event of disruptions

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## 10 Abstract

11 Little research has examined the behavior of public transport users in response to a service  
12 disruption that has just occurred. This article aims to identify the different ways in which  
13 suburban train passengers cope with service interruptions or delays and to identify the  
14 factors involved in their decision-making process. We conducted a study mixing two  
15 methods: a revealed-preference questionnaire that asked 185 participants about their  
16 choices during the last major disruption they encountered and a diary study in which  
17 participants described all disruptions they experienced during a two-week period. Eighty  
18 disruptions were reported in detail by 38 users. We analyze our results using multiple  
19 correspondence analysis and ascending hierarchical clustering to construct eight suburban  
20 train passenger behavioral profiles. Additionally, we compare different cases of disruption (in  
21 a multiple-case study). We identify three categories of factors affecting suburban train user  
22 behavior: individual-specific factors, journey-specific factors and information-specific factors.  
23 The findings show that user expertise, car availability, perception of service recovery time,  
24 opinions on passenger information services, available transport services, time constraints,  
25 and the moment and place at which communication about the disruption is received influence  
26 user behavior.

## 27 Keywords

28 User behavior, suburban train passenger choice, public transport, disruption, clustering, diary  
29 study.

## 30 1. Introduction

31 As of 2014, more than half of the world's population lives in cities (United Nations  
32 Department of Economic and Social Affairs, 2015). In 2050, this proportion is expected to  
33 rise to 66%. Paris has not avoided this trend. SNCF Transilien, which is one of the main

34 railway operators in the Greater Paris Region (Ile-de-France), has already had to cope with a  
35 30% increase in passenger traffic on its lines in the last 10 years. This trend is set to  
36 accelerate, but the existing infrastructure and resources are already being stretched by the  
37 increasing number of passengers. In an overcrowded public transport network, a disruption  
38 may have a significant impact on operators and users. Gaining a better understanding of the  
39 behavior of passengers in multimodal transport systems, particularly in the event of a  
40 disruption, has thus become crucial. Such an understanding could allow policymakers to  
41 predict this behavior, propose personalized alternative routes, adjust the capacity on some  
42 lines, and provide alternatives such as temporary shuttle buses.

43 The research presented in this article sets out to describe and understand the short-term  
44 behavior of suburban train (Transilien) passengers in response to unplanned short service  
45 disruption. Its results identify behavioral rules that cover the different ways of coping with  
46 service interruptions or delays. These rules were input into a multi-agent system within  
47 software that simulated a multimodal public transport network (Tschirhart, Adélé, Bauguion,  
48 & Tréfond, 2016). Compared to automobile user behavior, public transport user behavior in  
49 the event of a service disruption has received far less attention (Lin, Shalaby & Miller, 2016).  
50 Too few studies pay attention to passenger behavior and preferences (Teng & Liu, 2015), but  
51 adding passenger behavior (waiting, changing routes, using an alternative mode for  
52 traveling, cancelling trips) into transport modeling can improve predictions (Van der Hurk,  
53 Kroon, Li, Maroti, & Vervest, 2010). Moreover, most studies on disruptions that consider  
54 behavior have been conducted based on assumptions instead of empirically measured  
55 behavior (Lin, Srikukenthiran, Miller & Shalaby, 2018). Studies are also usually operator  
56 rather than passenger oriented (Golightly & Dadashi, 2017; Pender, Currie, Delbosc &  
57 Shiwakoti, 2013; Piner & Condry, 2016).

58 In this study, a disruption is seen as an incident-related occurrence that causes more or less  
59 severe delays or service interruptions on one or two of three suburban train lines in the Ile-  
60 de-France Region. These disruptions could be considered small in scale as they concern  
61 only a suburban line in a network (as opposed to large-scale long-term disruptions, as  
62 reviewed by Zhu & Levinson, 2012). This research attempts to understand the immediate  
63 decision-making of suburban train users if their usual public transport route is no longer  
64 available in the short term or their travel time via their usual public transport route is  
65 increased because of an unexpected disruption. In other words, it focuses on situations in  
66 which a disruption has just occurred and has been communicated to users. It also aims to  
67 specify the individual and situational factors related to users' behavioral responses. To meet  
68 this objective, the research focuses on users' reactions to disruptions lasting from five  
69 minutes to less than one day (which occur more rarely) for technical (i.e., signals, power

70 supply or track problems) or human reasons (rail suicide). These disruptions occur mostly on  
71 usual routes to or from work/school and are discovered at different stages of the trip (before  
72 starting the trip, at the departure station or en-route). Finally, passengers may have different  
73 levels of information about the cause, type or duration of the disruption. This paper  
74 comprises five sections. First, it presents a review of the current knowledge in the area of  
75 decision-making, the factors that influence choices and the measurement techniques used to  
76 study this topic. The second section outlines the procedure, the material and the sample  
77 used to conduct our study. The third section presents our empirical findings. Section four  
78 presents a discussion that situates our findings in relation to previous studies and describes  
79 the limits of our research. In the conclusion, we describe the principal contributions of this  
80 work and some perspectives.

## 81 **2. Literature review**

82 Since the initial work on individuals' absolute rationality, it has been accepted that there are  
83 limitations to decision-making. This theory of bounded rationality (Simon, 1955) postulates  
84 that decision-makers simplify their decisions, seeking satisfaction rather than optimization,  
85 and they make use of judgment heuristics, i.e., approximations based on experience.  
86 Individuals grasp the first alternative that is "good enough", according to their expectations.  
87 Individuals therefore seek a solution at the equilibrium between the time and effort required  
88 to find the solution and the solution's quality by applying the principle of cognitive economy  
89 (Chorus, Arentze, Molin, Timmermans, & Van Wee, 2006a). Factors such as past  
90 experience, habit, or uncertainty influence this search for a sufficiently good solution. Habit  
91 inhibits active decision-making (Van der Horst, 2004) and the tendency to explore unfamiliar  
92 parts of a transportation network (Chorus, Molin, & Van Wee, 2006b). A behavior becomes  
93 automatic when a decision reached by deliberation is considered to be satisfactory and the  
94 need to seek alternatives is lessened (Gärling, Fujii, & Boe, 2001; Marsden & Docherty,  
95 2013; Schwanen, Banister, & Anable, 2012; Verplanken, 2006). Like habit, uncertainty  
96 influences decision-making during a situation involving a disrupted trip because the exact  
97 characteristics of the alternatives (actual journey times, ridership) are in principle unknown  
98 (Chorus, Arentze, Timmermans, & Van Wee, 2007). In view of this ignorance, individuals  
99 assess the cost/benefit ratio for the alternatives they consider on an uncertain basis (Bonsall,  
100 2004).

101 The behavior of public transport users in response to a disruption has received little attention  
102 to date, and "the complexity of decision making of public transport user shows that empirical  
103 studies are needed to gain a better understanding" of this topic (Lin & al, 2016, p. 2).  
104 Numerous studies have focused on the behavior of car drivers. Although some of these

105 results may be relevant to our research, transport users and car drivers have different  
106 options and behavioral determinants in disruptive situations because two different groups  
107 (public transport and road users) with different characteristics are targeted (Nguyen-Phuoc,  
108 Currie, De Gruyter & Young, 2018a). Public transport users are often captive users because  
109 the majority of them have no alternative mode of transport (Van Exel & Rietveld, 2001).  
110 Moreover, the consequences of disruptions on road networks and public transport networks  
111 are different due to the latter's smaller size and limited number of alternative routes. Finally,  
112 the flow of information about disruptions is not the same on road and public transport  
113 networks. Information on road disruptions is usually more readily available to drivers (Lin &  
114 al., 2016). Despite these differences, it is interesting to consider the numerous studies  
115 focusing on the impact of a disruption on drivers' behavior. In this area of research, a  
116 considerable body of work has focused on the role of sociodemographic characteristics such  
117 as age, gender (Zhang, Yun, & Yang, 2012), or socio-occupational group on behavior  
118 (Emmerink, Nijkamp, Rietveld, & Ommeren, 1996). Travelers' levels of habit and experience  
119 have also frequently been used to explain their behavior (Bonsall & Palmer, 1999; Elia, Erev,  
120 & Shifan, 2008; Gärling & Axhausen, 2003). More rarely, research has linked behavior with  
121 personality, particularly sensation seeking (Shifan, Bekhor, & Albert, 2011). According to the  
122 designer of the Sensation Seeking Scale, sensation seeking is "a personality trait defined by  
123 the seeking of varied, novel, complex, and intense sensations and experiences, and the  
124 willingness to take physical, social, legal and financial risks for the sake of such experience"  
125 (Zuckerman, 1994, p.27.) Shifan, Bekhor and Albert (2011) have confirmed that a high level  
126 of sensation seeking tends to influence route choice, encouraging the selection of shorter but  
127 more variable routes. In addition, situational factors relate to the characteristics of a specific  
128 journey, such as trip purpose, distance, time of day (peak or off-peak periods), type of  
129 destination and the need to arrive on time (Peirce & Lappin, 2004). With regard to  
130 information, existing research has focused on when it is received (Jou, 2001; Polak & Jones,  
131 1993), its content and form (Bonsall & Palmer, 1999; Kitamura, Jovanis, Abdel-Aty, Vaughn,  
132 & Reddy, 1999; Van Berkum & Van der Mede, 1999), its quality, and how passengers react  
133 to it (Chorus, Molin, & Van Wee, 2006b; Khattak, Yim, & Stalker, 1999; Peirce & Lappin,  
134 2004). With regard to the moment at which information is received, Polak et Jones (1993)  
135 suggested that the earlier information is given, say, when individuals are still at home, the  
136 more choices are available to them (from cancelling the journey to changing their route,  
137 departure time or transport mode). This early step of the trip is called the "pre-trip" (Lin & al.,  
138 2016).

139 The subject of public transport users' choices has been explored particularly in relation to  
140 public transport strikes (Nguyen-Phuoc & al., 2018a, 2018b ; van Exel & Rietveld, 2001,

141 2009). Public transport strikes often result in complete service withdrawal. They affect not  
142 only passengers' usual routes but all public transit routes for one or more modes. Strikes can  
143 last a few days to a few weeks. Van Exel and Rietveld (2001) reviewed 13 studies of public  
144 transport strikes. The strikes lasted from one week to one month and affected all public  
145 transport modes in 8 cases and the entire network of one mode in 5 cases. In response to  
146 strikes, users must find a long-term solution. In our case, an unexpected disruption affects a  
147 passenger's usual route for a short time, but other public transport solutions are still  
148 available. Passengers choose from large set of possibilities within or outside of the public  
149 transport system. Another main difference exists between strikes and the kind of disruption  
150 we choose to study, which is that strikes are mostly announced (van Exel & Rietveld, 2009).  
151 In France, strikes must be announced two days beforehand by workers, and a precise  
152 schedule is communicated to users the day before the strike begins. This allows time for  
153 users to analyze the situation and the alternatives. In contrast, in the case of an incident, a  
154 disruption has just occurred and has been communicated, and users immediately engage in  
155 decision-making process with a limited number of options while in a particular emotional  
156 state. Nevertheless, we find that the study of the 1999 train strike in the Netherlands is  
157 relevant for our study (Van Exel & Rietveld, 2001). In this case, the first day of strike was  
158 unannounced because it was the result of violence against personnel. This strike lasted a  
159 few hours during morning peak time. There was no service in some regions, and there were  
160 severe delays in other regions. The information was poor or absent. One week after this  
161 strike, researchers surveyed 166 travelers and observed different behavioral adaptations for  
162 only approximately half of the commuters; these commuters cancelled their trip (10%), left  
163 home later (18%) or earlier (10%), or changed their travel mode (19%). The researchers  
164 highlighted the high level of inertia of commuters. The last difference between strikes and  
165 disruptions is that disruptions can occur at different steps of the trip, that is, before leaving  
166 home (pre-trip) or after leaving home (en-route), while passengers usually know about strikes  
167 before they leave home. Existing research findings identify interesting explanatory factors of  
168 strike effects on passenger behavior, highlighting three categories of factors (Nguyen-Phuoc  
169 & al., 2018a): individual-specific factors, context-specific factors, and journey-specific factors.  
170 Individual-specific factors are car ownership, driver's license ownership, number of cars  
171 available in the household, number of adults in the household, and income. Context-specific  
172 factors are travel distance, travel time, travel cost, trip destination, weather, and flexibility.  
173 Journey-specific factors are accessibility to public transport stations and trip purposes.  
174 Concerning context-specific factors, Nguyen-Phuoc et al. (2018a) showed that a trip  
175 destination in a city center implies difficulties related to parking and congestion, which make  
176 the choice of traveling by car less suitable. Regarding the trip purpose (journey-specific  
177 factor), cancellations primarily occur for leisure trips, education-based trips, and work-related

178 trips if the company allows employees to work from home. To the best of our knowledge, two  
179 studies have examined the impact of unexpected short-term disruptions on behavior, one in  
180 Calgary, Canada, and one in Toronto, Canada. The first performed a stated preference (SP)  
181 survey (Khattan & Bai, 2018). The second used a combination of revealed preference (RP)  
182 and SP surveys (Lin & al., 2018). In the first study, light rail transit passengers were asked  
183 about their behavior in disruption scenarios of different levels of severity and with different  
184 levels of information. Khattan and Bai (2018) proposed different explanatory factors of  
185 declared behavior, such as household vehicle ownership, the experience of the user,  
186 characteristics of other public transit paths (bus accessibility, location of the station, parking  
187 at the station), and the severity of the disruption. In that study, severity depended on the type  
188 of disruption (delay, interruption) and the service recovery time. In the second study, Lin et  
189 al. (2018) used questions about respondents' most recently encountered Toronto subway  
190 service disruption to enrich an SP experiment. The RP survey included questions about the  
191 origin and destination of the regular commuting trip (the characteristics of the trip were  
192 calculated by the Google Maps API), user characteristics (driver's license and vehicle  
193 access), disruption characteristics (date, time, location, type, duration) and behavior (mode  
194 chosen, additional travel time). Disruption scenarios were then generated for the SP  
195 experiment. RP and SP data revealed a mode split: 66% of the users chose to wait for the  
196 subway in the RP study, while only 11% did so in the SP study. A major limitation is that this  
197 study provided no information about the link between the delay (the severity of the disruption)  
198 and user behavior. The researchers chose not to ask respondents these questions for two  
199 reasons: it would have been difficult for them to remember this information, and, more  
200 importantly, they could have given post-incident information that was not available when they  
201 originally made their choices. Even if the cultural and infrastructural contexts and the  
202 methodology of these studies were different, they can serve as a basis for identifying which  
203 factors to explore.

204 Some studies consider all transport system users, including drivers and public transport  
205 passengers. They focus mainly on major natural disruptions. In a review, Zhu & Levinson  
206 (2012) identify three behavioral effects—route change, departure time and mode shift—in the  
207 case of long-term and large-scale disruptions such as transit strikes, bridge closures, special  
208 events generating a higher transport demand, and earthquakes. In general, the most  
209 common adaptations concern route and travel time change, “while the magnitude of changes  
210 varies depending on the context” (Zhu & Levinson, 2012, p.15). Zanni & Ryley (2015)  
211 examine long-distance traveler attitudes and past responses to disruptions caused by  
212 extreme weather events (snow) or other natural causes (volcanic ash, hurricanes) through an  
213 internet-based survey in the United Kingdom. They attempt to understand individual,

214 informational and contextual explanatory factors of this behavior, describing it as no change  
215 (chosen by the majority of respondents), time change, day change, cancellation, route  
216 change, destination change, departure point change, mode change, and companionship.  
217 Explanatory factors are the importance of the trip (linked with the purpose) and the severity  
218 of the disruption. The authors highlight the differences between the kind of trips they study  
219 and other types of trips, such as commuting, “with obviously different implications”. Brazil,  
220 Caulfield & O’Connor (2017) test pre-trip and on-trip hypothetical scenarios of weather  
221 disruption (heavy snow) to identify user behavior on different transport modes (car, rail and  
222 bus). For pre-trip scenarios, they find an impact of users’ transport habits and gender. Lastly,  
223 Marsden, Anable, Shires and Docherty (2016) examine the behavioral response of travelers  
224 on different modes to major disruptions (snow and ice, flooding, bridge closure) based on  
225 multiple surveys administered during disruptions. Their method is novel because almost all  
226 the data in the literature are based on hypothetical scenarios, which have poor ecological  
227 validity, or post-event surveys, which are affected by recall and reconstruction biases. The  
228 data they obtain highlight interesting explanatory factors, including distance traveled, reason  
229 for the trip, time since the beginning of the disruption, type of disruption, experience with  
230 similar situations, level of multi-modality, employer attitude toward changing working  
231 patterns, and social networks. Observed behaviors for commute trips are mainly delayed  
232 starts and cancellations. Even if the disturbances studied in these works are very different  
233 from those that interest us in terms of space and time scales, the results obtained contain  
234 relevant elements to guide our work.

235 Psychological studies in transportation often use market segmentation to describe and  
236 explain passenger behavior. Such studies reduce the complexity and heterogeneity of the  
237 whole population by dividing it into relevant subgroups (Pronello & Camusso, 2011; Anable,  
238 2005; Hunecke, Haustein, Bohler & Grischkat, 2010). Post hoc groups are specified on the  
239 basis of empirical results. Individuals are grouped with a cluster analysis according to their  
240 similarity in a specific set of variables. Haustein and Hunecke specify that “none of the  
241 approaches can claim absolute superiority. Instead, they show specific pros and cons, which  
242 suggests an application in different fields of the planning and design of mobility measures”  
243 (2013, p.201). In our study, we use post hoc behavioral segmentation based on empirical  
244 results, as our aim is to provide useful information for the creation of a realistic simulation  
245 tool. In addition to behavioral variables, socio-demographic, attitudinal, infrastructural and  
246 geographical variables are included in the analysis to overcome the oft-reported limitation of  
247 behavioral segmentation, that is, its lack of explanation of behavior (Hunecke & al., 2010).

248 At a methodological level, existing studies are largely based on two widely used approaches:  
249 SP and RP methods (Peeta & Ramos, 2006). SP methods analyze an individual’s behavior

250 by presenting him or her with a series of hypothetical alternatives relating to a fictional  
251 journey presented in the form of a scenario (Nguyen-Phuoc & al., 2018b). This is the  
252 approach most frequently applied in transportation studies (Emmerink et al., 1996; Polak &  
253 Jones, 1993). While the presentation of fictional situations facilitates the administration of  
254 surveys and the analysis of results, the ecological validity of the findings is poor (Chorus,  
255 2012). RP approaches analyze behaviors in real situations based on, for example, daily  
256 travel diaries, observations, or surveys that relate to past behaviors (Marsden & al., 2016).  
257 Studies using RP provide data that are of good quality because they are more realistic  
258 (Bonsall & Palmer, 1999), but RP can only be used to investigate phenomena that occurred  
259 during or shortly before the studied period. Some research uses interviews in addition to  
260 scenarios (Nuguyen-Phoc & al., 2018a) or lived past situations (Grison, Gyselinck &  
261 Burkhardt, 2016). Despite the limitations of this approach, we chose to focus on real  
262 situations of disruption by using a combination of methods: RP surveys related to past  
263 behaviors and diary studies related to repeated actual behaviors (Bolger & Laurenceau,  
264 2013). A diary was already performed to study behavioral adaptation in the case of strikes  
265 (Bonsall & Dunkerley, 1997). The original aim of this study was to use concessionary travel  
266 permits for the elderly and people with disabilities in London. The diary survey period  
267 contained 6 days of an underground strike. Through a comparison, the researchers were  
268 able to highlight the impact of the strike on the travel behavior of this particular population;  
269 this behavior included a reduction in the number of trips and an increase of bus use. In our  
270 diary study, only disrupted trips were recorded. Every situation of an identified user facing a  
271 precisely characterized disruption was studied. This method could be considered as a  
272 multiple-case study, with one case being represented by one individual in different situations  
273 of disruption or different individuals in the same or similar situations of disruption. Case  
274 studies do not allow generalization of the results (Baxter & Jack, 2008) but permit the  
275 proposal of in-depth ecologically valid results on a sample that is limited and not always  
276 representative. According to Yin (2003), a case study is useful to explore a situation in which  
277 behavior cannot be manipulated and to cover contextual conditions that are relevant to the  
278 phenomenon under study. We use a multiple-case study to explore situational and individual  
279 differences between cases. The evidence created from this type of study is considered  
280 robust and reliable (Baxter & Jack, 2008).

281 The major aim of the study presented in this paper is to describe, analyze and understand  
282 the behavior suburban train passengers engage in to cope with disruptions that vary in their  
283 cause and severity. This study attempts to answer different questions: What would suburban  
284 train users do if their usual public transport route were no longer available in the short term  
285 because of a disruption? What would they do if their travel time via their usual public

286 transport route were higher because of an incident? What are the main factors affecting  
287 people's choices in these contexts? To reach our goal, we decided to study a set of  
288 dimensions that have already been identified in the literature. The conceptual model consists  
289 of multidimensional factors affecting suburban trains users' choices. These factors can be  
290 classified into three categories: individual-specific factors (including personality and  
291 opinions), journey-specific factors, and information-specific factors. These dimensions will be  
292 described in detail in the "Material" section below.

### 293 **3. Method**

294 To capture the behavior of suburban train passengers and their determinants, we designed a  
295 research procedure that comprised two steps. For greater clarity, we begin by presenting this  
296 procedure and then describe the measurement tools, followed by the selected sample.

297

#### 298 **3.1. Procedure**

299 A survey was conducted among suburban train passengers who travelled at least once a  
300 month on a selected part of the Transilien network (lines U, C and N). In view of feasibility  
301 constraints, and to obtain realistic results, a two-phase survey was carried out. The first  
302 online questionnaire (Phase 1), which respondents completed only once, aimed to  
303 characterize respondents and their travel habits under normal and severely disrupted  
304 conditions. A section was added at the end of the questionnaire to recruit volunteers for the  
305 diary study. Respondents indicated whether they would agree to receive an email invitation  
306 to participate in the second phase of the study. The diary study (Phase 2) was then  
307 presented to the Phase 1 respondents who were willing to continue the survey. The diaries  
308 were to be filled in by the respondents within five minutes over a period of two weeks  
309 (outside school holidays) each time they felt they had been affected by an unplanned  
310 disruption on the studied lines, of whatever severity or cause. This diaries enabled us to  
311 establish a link between a specified disruption and the behavior of individual passengers.  
312 The two phases were administered online via the FluidSurveys website. On this website, we  
313 could modify the way the questionnaire and the diary were displayed to suit the type of  
314 device used by the respondents, i.e., a computer, smartphone or tablet. The survey provided  
315 no incentive to respondents beyond the possibility of receiving a summary of the results if  
316 they so wished.

##### 317 **3.1.1 Questionnaire 1**

318 To contact users by email, we extracted individuals from a commercial database of adult  
319 holders of the public transportation card Navigo<sup>1</sup>, all of whom were willing to be contacted for  
320 such purposes. As the database does not contain any information on the mobility habits of  
321 users, we had to perform approximations to target individuals who used the three relevant  
322 train lines in applying a filter based on the municipality of residence (the only information we  
323 had). In total, 28,236 users living in 65 municipalities were contacted on March 5, 2015,  
324 through an email that contained a link to Questionnaire 1. Eighty percent of the users of the  
325 three lines studied live in these municipalities, according to the origin-destination survey of  
326 the operator<sup>2</sup>. A personalized reminder was sent out on March 13. At the end of the 15-day  
327 survey period, on March 19, 2,708 respondents were counted (a return rate of 9.59%), of  
328 whom only 200 passed the screening process (line used and travel frequency) and  
329 completed the questionnaire. Our final sample comprised 185 respondents who adequately  
330 completed the questionnaire (a response rate of 0.65%) on the basis of a quality check  
331 process (consistency of the answers and a lack of stereotyped answers).

### 332 3.1.2 Diary study

333 An email containing a link to the diary study was sent on March 20 to the respondents who  
334 were willing to take part in Phase 2. The diary was filled in by 38 participants during an 18-  
335 day period from March 20 to April 6. Fifteen respondents completed the diary several times,  
336 and one participant completed it as many as seven times. Two reminders were sent out on  
337 March 25 and 30.

## 338 3.2. Material

339 The questionnaire and the diary were drafted based on the analysis of the current state of  
340 knowledge and 28 semi-directive interviews with regular and occasional users of the studied  
341 lines and French and foreign tourists (Martin, Adélé, & Reutenauer, 2016).

### 342 3.2.1 Questionnaire 1

343 The first questionnaire took an average of 20 minutes to fill in and aimed to gain knowledge  
344 about the respondents and their perceptions. First, it enabled us to collect information on the  
345 suburban train passengers' past behavior in highly disruptive situations. The definition of a  
346 highly disrupted situation was deliberately left up to the individual respondent and gauged by  
347 a specific question. Respondents were also asked to estimate the frequency of disruptions

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<sup>1</sup> The Navigo card offers unlimited travel by all public transport modes (bus, metro, suburban trains, tramway) in selected zones on a period from one week to one year.

<sup>2</sup> 12264 respondents spatiotemporally representative of the users of the three lines studied with corrective weights applied on the basis of manual counts on a business day

348 on their customary journeys and to describe the impact of these disruptions on their daily  
349 lives. They also reported the alternatives that were available to them in the event of a major  
350 disruption on their customary journey in both the outbound and return directions. The  
351 alternatives that were presented were as follows: changing routes while staying on public  
352 transport, changing modes (using a car, a motorized two-wheeler, or a bicycle or walking  
353 instead of using public transport), changing destinations, cancelling the trip (teleworking,  
354 taking a day off), and waiting. Respondents could give several responses. Then, a number of  
355 questions addressed the use and nature of other routes in the event of a disruption, the  
356 frequency with which the respondents changed route and the link between delays and such  
357 changes, with or without a time constraint. Part of the questionnaire was devoted to  
358 respondents' habits with regard to passenger information. They were thus asked whether  
359 they had subscribed to commuter service alerts, how frequently they consulted commuter  
360 information services, and what their opinion was on the information. They were also asked to  
361 state what information they usually received in the event of a disruption. Lastly, the  
362 questionnaire allowed us insight into the personality of the respondents by incorporating  
363 questions relating to the Sensation Seeking Scale developed by Zuckerman, Kolin, Price, &  
364 Zoob (1964) and modified by Outwater, Castleberry, Shiftan, Ben-Akiva, Zhou, & Kuppam  
365 (2003) as well as their individual characteristics such as age, gender, socio-occupational  
366 group, residential location and place of work. Passengers also answered questions about  
367 their opinions about their public transport journeys, the routines they employed during their  
368 trips and their level of knowledge about the network.

### 369 3.2.2 Diary study

370 To compensate for the recall nature of the first questionnaire, we used a diary to gather data  
371 in respondents' natural, spontaneous context. The aim was to establish a link between a real  
372 situation of disruption, of whatever level of severity, and an adopted behavior. During the  
373 study period, participants were able to fill in the diary each time they felt their trips had been  
374 affected by an unplanned disruption. The diary was designed to take less than five minutes  
375 to complete while still providing important information for the study, that is, the trip made, the  
376 disruption experienced (place, moment of communication, cause, type, duration), the  
377 information received, and the decision made by the respondent in response to this disruption.

378 To link the information given by the respondents to the situation of disruption, we also used  
379 data from the operator database. This database gives all information about each train that  
380 should have circulated on each day and line. This allowed us to assign different diary entries  
381 at the same event with more certainty.

### 382 3.3. Sample

### 383 3.3.1 Questionnaire 1

384 For Phase 1, the sample consisted of 185 respondents, 56% of whom were women. The  
385 sample was broken down into several age groups: 38% of the respondents were between 18  
386 and 25 years old, 21% were between 26 and 39 years old, 35% were between 40 and 59  
387 years old, and 6% were over 60 years old, for an average age of 35. The sample consisted  
388 of 37% executives, 26% intermediate professions, 33% students and 4% people who were  
389 not employed. Sixteen percent of the respondents lived in Paris, 14% lived in the inner  
390 suburbs, and 70% lived in the outer suburbs. Within the sample, line N was the most  
391 commonly travelled line, accounting for 40% of the respondents, while lines C and U  
392 accounted for 23% and 15%, respectively. The remaining 22% of the sample principally used  
393 a combination of lines. On average, respondents' commute involved three separate modes,  
394 with 1.2 transfers between two modes of public transport or two lines. The trips lasted an  
395 average of 67 minutes, rising to 84 minutes in the event of disruptions. Of the respondents,  
396 62% had been making this journey for more than a year.

397 To test the representativity of the sample, the sample was compared to figures collected in  
398 surveys conducted by Transilien<sup>3</sup> (more than 10,000 passengers surveyed within our study  
399 zone) with regard to a number of criteria: frequency of use, journey time, number of modes  
400 used, gender, age, socio-occupational group, principal line used, station of origin, and  
401 experience. In our sample, users of lines N and U were overrepresented compared with  
402 users of line C. Women were also overrepresented. In addition, students were  
403 overrepresented relative to economically active and inactive individuals. The "abnormal"  
404 distribution of socio-occupational groups can probably be explained by the dissemination  
405 mode we selected. Students and executives are perhaps the groups that are the most  
406 familiar with the internet and smartphones. Furthermore, the average age was slightly high,  
407 and the age distribution was atypical: the 26-39 age group was underrepresented, while the  
408 18-25 age group and, above all, the 40-59 age group were overrepresented.

### 409 3.3.2 Diary study

410 Out of the 185 respondents in Phase 1, 38 reported between 1 and 7 disruptions. A total of  
411 80 disruptions were reported during Phase 2, which ran from March 20 to April 6. The  
412 sample for Phase 2 matched that for Phase 1 fairly closely. Compared with the sample in the  
413 Transilien surveys, our sample was slightly more representative with regard to the age and  
414 socio-occupational group of the respondents. However, there were still too few 26-39-year-  
415 olds and too many executives.

---

<sup>3</sup> For reasons of confidentiality, the precise characteristics of the reference population have not been stated.

### 416 3.4 Data analysis design: questionnaire 1

417 In our research, understanding the choices of public transport passengers during disruptions  
418 using the questionnaire required three steps. The first step was the identification of variables  
419 with an impact on behavior, mainly with  $\chi^2$  analysis. The second step was to identify the  
420 pattern of relationships of several categorical variables (behavioral variables) to be  
421 interpreted by the use of multiple correspondence analysis. The third step was to define  
422 homogeneous groups of users through cluster analysis.

## 423 4. Results

### 424 4.1. Results from Questionnaire 1

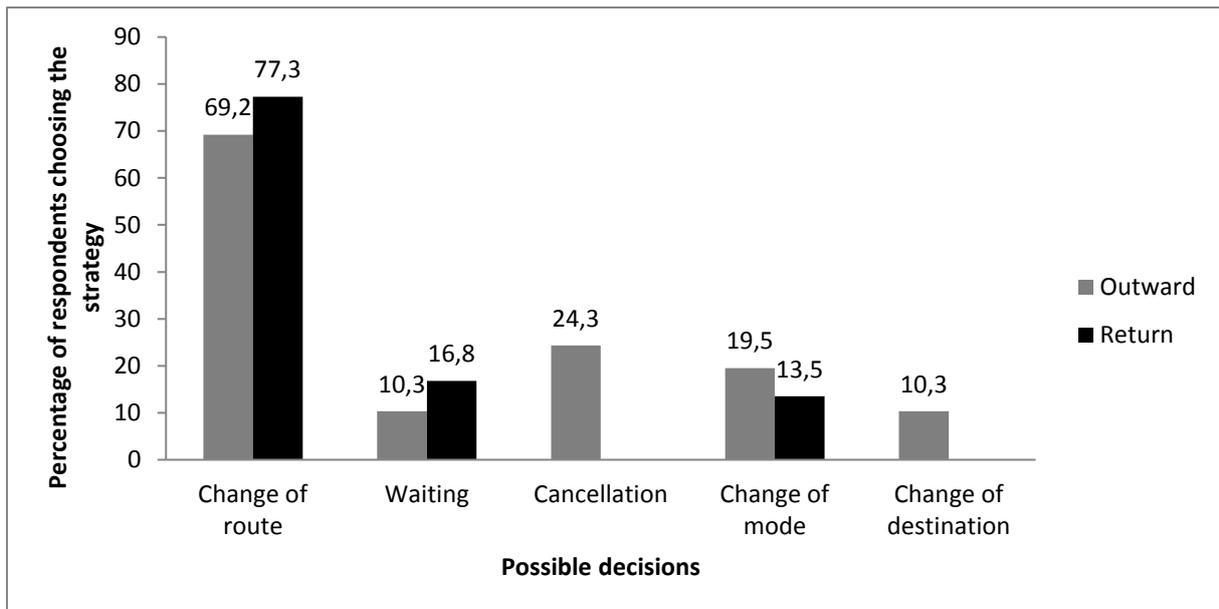
#### 425 4.1.1. Descriptive results: What did suburban train users tell us about their behavior 426 during disruptions?

427 The results presented in this section were obtained with SPSS© software.

- 428 • Decisions in the case of major disruptions on the outbound or return journey (Fig. 1)

429 Most of the respondents stated that they changed routes in the event of a major disruption  
430 (defined as a delay of more than 30 min by 70% of the respondents). This applied to almost  
431 70% of the respondents on the outbound journey and slightly over 77% on the return journey.  
432 Very few respondents waited in these situations (10.3% on the outbound journey and 16.8%  
433 on the return journey). In addition, on the outbound journey, 24% of the respondents either  
434 decided not to travel (taking the day off or teleworking) or changed their destination. On the  
435 outbound journey, 19.5% of the respondents transferred to another mode, compared with  
436 only 13.5% on the return journey. The mode changes on the return journey often involved  
437 calling on assistance from a third party (a family member, taxi or car-sharing).

438



439  
 440 **Fig. 1. Decisions reported by respondents in the event of major disruptions according to their direction of travel**  
 441 **(multiple-choice question)**

442

- 443 • Waiting time before changing routes with and without time constraints

444 The declared waiting times before changing routes were significantly different depending on  
 445 whether the passengers had time constraints. The waiting time in the absence of time  
 446 constraints was generally higher than that in the presence of time constraints ( $Z = -3.68$ ;  $p$   
 447  $<.001$ ).

- 448 • Route change

449 The occurrence of a disruption affects the route chosen by suburban train passengers.  
 450 Journey times increased to an average of 84 minutes during disruptions from an average of  
 451 67 min in normal situations ( $Z = -7.21$ ;  $p < .001$ ). Moreover, in disruptive situations, the  
 452 change in route altered the departure and arrival stations in 62% of cases. Depending on the  
 453 distance, passengers went to the new station either on foot (a maximum distance of 1.8 km)  
 454 or by car (a maximum distance of 13 km). The modes used were also different: private car (+  
 455 86 %), bus (+ 19 %), metro (+ 31 %), and tram (+ 567 %). However, a disruption did not  
 456 necessarily lead to more transfers during the journey. The usual route involved 1.2 transfers,  
 457 while the alternative route involved 1.8 transfers on average.

#### 458 **4.1.2. Bivariate analyses: How can we explain these behaviors?**

459 We have attempted to identify what individual-specific, journey-specific or information-  
 460 specific factors explain the different reactions with regard to the major disruptions. The  
 461 statistical analyses were conducted using SPSS© software.

- 462 • Individual-specific factors

463 With regard to individuals, we have demonstrated the impact of household car ownership  
 464 (access to a car) (Table 1). Those with access to a car use more the solution to change  
 465 mode ( $\chi^2(1)=22.27$ ;  $p<.001$ ) and less the solution to change route ( $\chi^2(1)=7.84$  ;  $p<.01$ ) than  
 466 others on outbound trips. Access to a car is associated with differences related to age and  
 467 socio-occupational group. More specifically, the youngest respondents and students were  
 468 less able to change modes on their outbound journey. These groups had significantly less  
 469 access to a car than the others ( $\chi^2(3) = 15.24$ ;  $p = .002$ ).

470 **Table 1. Access to a car and behavior on the outbound trip (n=185)**

	<i>Change route</i>		<i>Change mode</i>	
	Yes (n=128)	No (n=57)	Yes (n=36)	No (n=149)
<b>Access to a car</b>				
Yes (n=82)	58%	42%	34%	66%
No (n=103)	78%	22%	7%	93%

471

472 We have also shown that the expertise of suburban train passengers has an impact. In  
 473 contrast to what we might have expected, the most experienced regular passengers (who  
 474 had been using their daily route for more than one year) were less proactive with regard to  
 475 seeking an alternative solution (Table 2). More particularly, a greater proportion of the most  
 476 experienced passengers chose to wait on the return journey ( $\chi^2(1) = 4.73$ ;  $p = .03$ ) and wait  
 477 longer than the others when they had no time constraints ( $\chi^2(2) = 6.48$ ;  $p <.05$ ) (Table 3).  
 478 Similar results were obtained with regard to passengers' level of habit (Table 2). A strong  
 479 habit leads to a greater propensity to wait on both the outbound journey ( $\chi^2(2) = 5.63$ ;  $p =$   
 480  $.06$ ) and the return journey ( $\chi^2(2) = 7.76$ ;  $p = .02$ ).

481 **Table 2. Experience with the route, level of habit and waiting behavior**

	<i>Outbound journey</i>		<i>Return journey</i>	
	<i>Wait</i>		<i>Wait</i>	
	Yes (n=19)	No (n=166)	Yes (n=32)	No (n=153)
<b>Experience with the route</b>				
≤ 1 year (n=62)		Not significant	9%	91%
>1 year (n=123)			22%	78%

Average level of habit				
Low (n=64)	3%	97%	6%	94%
Medium (n=48)	12%	88%	23%	77%
Strong (n=73)	15%	85%	22%	78%

482

483 **Table 3. Experience with the route and waiting time without time constraints**

	Waiting time without time constraints		
	Less than 15 min (n=54)	From 15 to 30 min (n=65)	More than 30 min (n=66)
<b>Experience with the route</b>			
≤ 1 year (n=62)	43%	30%	27%
>1 year (n=123)	22%	39%	40%

484

485 Finally, we have identified an impact of opinion on behavior (Table 4). A favorable opinion  
 486 toward traffic information leads to a greater tendency to change routes in the event of a  
 487 disruption on the return journey ( $\chi^2(2) = 8.05$ ;  $p = .02$ ).

488 **Table 4. Opinion toward traffic information and route change on the return journey**

	Change route	
	Yes (n=128)	No (n=57)
<b>Opinion toward traffic information</b>		
Negative (n=34)	73%	27%
Mixed (n=120)	73%	27%
Positive (n=31)	97%	3%

489

- 490 • Journey-specific factors

491 It seems to be clear that the opportunities for changing the route afforded by the transport  
 492 network significantly alter the behavior of suburban train users when confronted by a major  
 493 disruption. The position on the line is closely linked to the decision regarding whether to  
 494 change routes on both the outbound journey ( $\chi^2(2) = 16.98$ ;  $p < .001$ ) and the return journey  
 495 ( $\chi^2(2) = 6.99$ ;  $p = .03$ ). Comparing the respective numbers for these variables reveals that a  
 496 smaller proportion of individuals who started their journey at the end of the line reported  
 497 changing their route (Table 5). **Because the Ile-de-France transport network is highly**  
 498 **centralized, the passengers who live in remote outer suburbs have a low transport supply.**

499 **Table 5. Position of the departure station and route change behavior**

	Outbound journey	Return journey
--	------------------	----------------

	Route change			
	Yes (n=128)	No (n=57)	Yes (n=143)	No (n=42)
<b>Position on the line</b>				
Paris and inner suburbs (n=55)	75%	25%	85%	15%
Outer suburbs (n=68)	82%	18%	81%	19%
Remote outer suburbs (n=62)	50%	50%	66%	34%

500

- 501 • Information-specific factors

502 Our results reveal a link between changing modes on the outbound journey and subscribing  
503 to the notifications sent out by the operator ( $\chi^2(1) = 4, 01; p < .05$ ). People who subscribed to  
504 these services were more likely to change modes than persons who had not (Table 6).  
505 Furthermore, suburban train passengers who decided to wait in a disruptive situation on the  
506 return journey were unlikely to seek traffic information ( $\chi^2(1) = 5, 71; p < .02$ ) (Table 7).

507 **Table 6. Subscription to operator's notifications and mode change behavior on the outbound journey**

	Change mode	
	Yes (n=36)	No (n=149)
<b>Subscription to operator's notifications</b>		
Yes (n=90)	26%	74%
No (n=95)	14%	86%

508

509 **Table 7. Search for traffic information and waiting behavior on the return journey**

	Wait	
	Yes (n=32)	No (n=153)
<b>Search for traffic information</b>		
Yes (n=66)	5%	95%
No (n=119)	23%	77%

510

### 511 4.1.3. A multivariate analysis: Can we identify suburban train passengers' behavioral 512 profiles?

513 Questionnaire 1 was mainly composed of nominal categorical questions with a finite number  
514 of response categories or modalities. For this kind of variable, the multiple correspondence  
515 analysis (MCA) method is particularly suitable (Benzécri, 1992). Correspondence analysis is  
516 a statistical technique for categorical data that is often used in social sciences. It permits  
517 "more rapid interpretation and understanding of the data." (Greenacre, 2017, p.xi). MCA is a  
518 factorial method that (similar to other methods in this family, such as the well-known principal

519 component analysis) seeks optimal projections to summarize a dataset by exploiting the  
 520 redundancy between the variables. The main difference between it and PCA relates to the  
 521 nature of the processed data. MCA is performed by applying the correspondence analysis  
 522 algorithm to a Burt table. It assigns scores to rows (representing the subjects) and columns  
 523 (representing the response categories). MCA is largely descriptive (Le Roux & Rouanet,  
 524 2010), and it is suitable for small samples because correspondence analysis is based on  
 525 relative values. One question that arises when performing MCA concerns the number of  
 526 dimensions to keep. It is possible, for instance, to examine a scree plot of eigenvalues to  
 527 identify the elbow in descending sequences. The second question that arises is the  
 528 interpretation of the axes. This interpretation is based on the modalities whose contribution to  
 529 the axis exceeds their relative weight.

530 All respondents reported at least two behavioral choices for outbound and return trips, but  
 531 some reported more choices in the event of a major disruption. It is therefore relevant to go  
 532 beyond bivariate analysis and attempt to identify links between all behavioral variables. We  
 533 performed multivariate analysis by applying MCA (Benzécri, 1992) using SPAD© software.  
 534 The analysis included nine behavioral variables (route change, mode change, destination  
 535 change, waiting for the outbound and return trips, and cancellation of the outbound trip),  
 536 which have two modalities: yes/no. The aim of this analysis is to highlight similar patterns of  
 537 behavioral choices among users.

538 **Table 8. Results of the MCA, histogram of the first eigenvalues**

Axis	Eigenvalues	Percentage	Cumulative percentage
1	0.2694	26.94	26.94
2	0.1619	16.19	43.13
3	0.1439	14.39	57.52
4	0.1116	11.16	68.69

539

540 The MCA results (Table 8) show that axis 1 largely explains the differences between the  
 541 behavioral patterns in our sample. Although there is a considerable drop in the eigenvalues  
 542 between the first two axes, the results prompt us to choose three axes rather than two  
 543 because the “destination change on the return journey” and “cancellation on the outbound  
 544 journey” variables are mainly present on the third axis. To describe the axes, we consider the  
 545 modalities whose contribution exceeds their relative weight (Table 9). These axes are ways  
 546 to understand the behavior of our sample in simplifying the information we have about it. In  
 547 our case, we go from nine variables and eighteen modalities to 3 axes, each of them having  
 548 two sides.

549 **Table 9. Results of the MCA, relative weight and contributions of active variables (values in bold are used for the**  
 550 **interpretation of the axis)**

	Modalities	Relative Weight	Contribution axis 1	Contribution axis 2	Contribution axis 3
Outbound trip	Cancellation yes	2.46	0.4	0.2	<b>34.1</b>
	Cancellation no	8.65	0.1	0.1	<b>9.7</b>
	Route change yes	7.69	<b>7.6</b>	0.5	1.8
	Route change no	3.42	<b>17.0</b>	1.0	<b>4.1</b>
	Destination change yes	0.36	<b>1.2</b>	0.1	<b>12.8</b>
	Destination change no	10.75	0.0	0.0	0.4
	Mode change yes	2.10	1.6	<b>36.6</b>	0.3
	Mode change no	9.01	0.4	8.5	0.1
	Waiting yes	1.14	<b>16.7</b>	<b>8.3</b>	2.5
Waiting no	9.97	1.9	0.9	0.3	
Return trip	Route change yes	8.59	6.2	0.1	0.3
	Route change no	2.52	<b>21.3</b>	0.2	1.0
	Destination change yes	1.14	0.4	0.1	<b>27.6</b>
	Destination change no	9.97	0.0	0.0	3.2
	Mode change yes	0.66	0.8	<b>36.0</b>	0.0
	Mode change no	10.45	0.1	2.3	0.0
	Waiting yes	1.86	<b>20.2</b>	<b>4.2</b>	1.4
	Waiting no	9.25	4.1	0.8	0.3
Possible interpretation			Inaction/action	Car/no car	Flexibility/ constraints

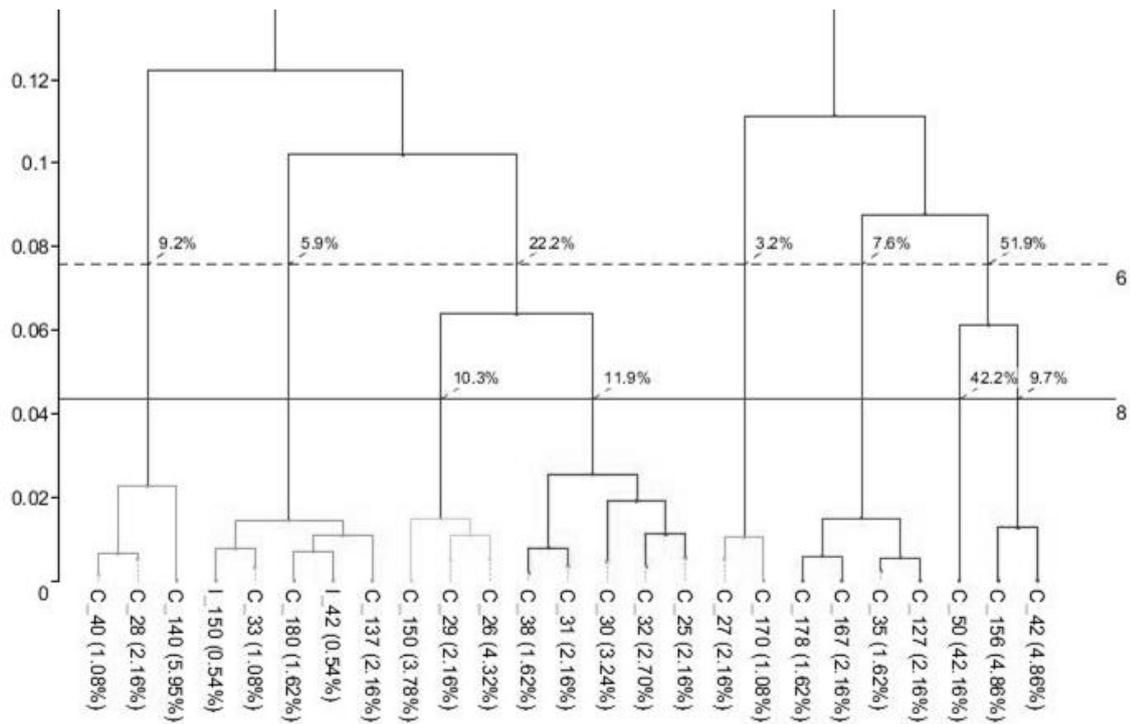
551

552 By considering the three axes, we can say that our sample can be described by three  
 553 dimensions: inaction or action (axis 1), car or no car available (axis 2), and possibility to  
 554 adapt planned activities at the destination or not (axis 3).

555 It is interesting to use the MCA results for clustering. Ascending hierarchical clustering (AHC)  
 556 is a way to define homogeneous groups of passengers on the basis of the three strategies  
 557 resulting from the MCA. We do so using the Ward aggregation index. At each step of the  
 558 clustering, the two closest individuals are grouped, hence the representation by a  
 559 hierarchical tree (dendrogram). Cluster analysis does not offer a test to calculate the optimal  
 560 number of clusters (Hunecke & al., 2010). It is possible to see the way the structure is formed  
 561 with the dendrogram and to select the optimal segmentation according to the hypotheses.  
 562 The interpretation of clusters relies on over- and underrepresented modalities by comparing  
 563 the relative frequency of the modality in the cluster and the frequency in the whole set (Le  
 564 Roux & Rouanet, 2010).

565 Then, the goal of the second phase of our work was to create a segmentation by hierarchical  
 566 clustering using SPAD©. The aim was to highlight the different groups of suburban train  
 567 users according to similar behavioral patterns as well as individual-specific (car access, age,  
 568 gender, socio-occupational group) or journey-specific (line used, position of the departure  
 569 station on the line) factors.

570 **Fig. 2. Part of the hierarchical clustering dendrogram of behavioral profiles**



571

572 We estimate that the best partition of individuals consists of 8 clusters because there is a  
 573 large jump from 0.02 to 0.06 in the dendrogram (Fig. 2). It would also be possible to choose  
 574 a partition in 6 or 2 clusters, but we prioritize having the finest description of the groups of  
 575 individuals. It is also notable that the smallest classes are still there in a 6-cluster partition.  
 576 The size of the clusters is not too small.

577 The 8 clusters correspond to 8 behavioral profiles in the event of a major disruption, as  
 578 defined in Table 3. By observing the modalities that are shared by the users in each cluster  
 579 that is overrepresented compared with the other clusters, we can describe the typical  
 580 behaviors and the characteristics that can be attributed to the cluster (Table 10).  
 581 “Teleworkers” (11%) were the only group in which no individual-specific or situation-specific  
 582 factor was salient. The cancellation of outbound trips was common to all members of this  
 583 group. Three groups shared a common way of coping with disruptions by changing routes;  
 584 these groups were the “route changers” (42%), the “flexible users” (9%) and the “leisure  
 585 users” (3%). The “route changers”, which comprised the major part of the sample, only

586 changed routes, while the other groups also used other ways of coping. The “route changers”  
587 did not live in the remote suburbs of Paris, where the transport system is less developed, and  
588 have a low access to a car. The “flexible users” are almost the only ones changing  
589 destinations on return trips. As these users are young and students, we think that they have  
590 less obligation to return home and have more opportunities to sleep at a friend’s. The “leisure  
591 users” have the widest selection of solutions to cope with disruptions on outbound and return  
592 trips but are statistically represented by destination changes on outbound trips. This cluster  
593 includes a higher portion of pensioners than the others. As the cluster also includes workers  
594 and students, we think that it could also be called the “desk-sharer” cluster to indicate that  
595 some of its members have multiple workplaces or places of study. “Car owners” (11%) and  
596 “passengers” (6%) share the use of the car as a solution, the first as drivers of their own car  
597 (only on outbound trips) and the second as passengers. “Car owners” have access to a car  
598 and are more likely to be men and executives. On return trips, they mostly change their  
599 route. “Passengers” are the only group changing modes on return trips. They mostly live in  
600 the outer suburbs, which is why we call them “passengers” and not “car borrowers”. The  
601 Autolib car-sharing service is only available in the inner suburbs and in Paris. The  
602 “constrained” group (9%) is the only group that mainly waits on outbound and return trips.  
603 They are mostly users of line N who live in the remote outer suburbs, where the transport  
604 system is less developed. Their range of solutions is wider for return trips. Individuals  
605 comprising the “passive on return trip cluster” almost all wait when an important disruption  
606 occurs on their return trip, while they do not wait on their outbound trip. We formulate the  
607 hypothesis that this group is composed of people with no familial or personal obligations in  
608 the evening. They prefer to use the waiting time to engage in other activities (such as having  
609 a drink or working longer).

610 **Table 10. Behavioral clusters identified from the results of Questionnaire 1 (values in bold indicate that the**  
611 **corresponding modality is overrepresented, and values in grey indicate that the corresponding modality is**  
612 **underrepresented in the cluster)**

Characteristics of the users	Clusters (%)							
	Teleworkers (n=20 ; 11%)	Route changers (n=78 ; 42%)	Flexible (n=16 ; 9%)	Leisure users (n=6 ; 3%)	Passive on return trip (n=16 ; 9%)	Car owners (n=21 ; 11%)	Passengers (n=11 ; 6%)	Constrained (n=17 ; 9%)
<i>Gender</i>								
Male	45.0	46.15	18.75	33.33	37.5	<b>66.66</b>	36.36	41.18
Female	55.0	53.85	81.25	66.67	62.5	33.34	63.64	58.82
<i>Age</i>								
18–25	30.0	37.18	<b>68.75</b>	50.0	50.0	14.29	45.46	17.65
26–40	25.0	20.51	18.75	16.66	12.5	23.81	18.18	29.41
41–60	30.0	35.90	6.25	16.67	37.5	57.14	18.18	47.06
60+	10.0	3.85	6.25	16.66	0	4.76	18.18	5.88
<i>Behavior in case of major disruption</i>								
Route change - outbound	50.0	<b>100</b>	68.8	83.3	50	38.1	54.5	11.8
Mode change - outbound	<b>0</b>	<b>0</b>	6.3	16.7	31.3	<b>100</b>	<b>72.7</b>	0
Waiting - outbound	0	<b>0</b>	6.3	0	0	0	9.1	<b>100</b>
Destination change - outbound	0	0	0	<b>100</b>	0	0	0	0
Cancellation - outbound	<b>100</b>	<b>0</b>	43.8	100	43.8	9.5	18.2	5.9
Route change - return	90.0	<b>100</b>	68.8	100	12.5	<b>85.7</b>	45.5	29.4

Mode change - return	20.0	<b>2.6</b>	12.5	0	6.3	19.0	<b>100</b>	5.9
Waiting - return	<b>0</b>	<b>0</b>	0	0	<b>93.8</b>	14.3	0	<b>76.5</b>
Destination change - return	0	<b>0</b>	<b>100</b>	33.3	0	0	9.1	0
<i>Line usually used</i>								
Line N	33.3	39.1	50.0	25.0	42.9	61.1	30.0	<b>93.3</b>
Line U	13.3	21.7	14.3	0	21.4	16.7	20.0	0
Line C	33.3	30.4	28.6	7.5	28.6	16.7	20.0	0
Combination of lines N 1 C	20.0	8.7	7.1	0	7.1	5.6	30.0	6.7
<i>Employment position</i>								
Manager	50.0	34.6	6.3	16.7	25.0	<b>61.9</b>	27.3	56.3
Technician	5.0	7.7	6.3	0	6.3	9.5	0	6.3
Employee	10.0	20.5	12.5	16.7	18.8	19	<b>36.4</b>	12.6
Student	30.0	34.62	<b>68.75</b>	50.0	50.0	9.5	27.27	17.65
Unemployed	0	1.3	0	0	0	0	9.1	6.3
Pensioner	5	1.3	6.3	<b>16.7</b>	0	0	0	0
<i>Access to a car</i>								
Yes, always	40.0	17.9	18.8	16.7	31.3	<b>57.1</b>	36.4	29.4
Yes, often	10.0	14.1	6.3	16.7	25.0	33.3	0	23.5
Yes, rarely	15.0	24.4	18.8	16.7	12.5	4.8	18.2	17.6
No	35.0	43.6	56.3	50.0	31.3	4.8	45.5	29.4
<i>Position of the departure station</i>								
Remote outer suburbs	30.0	23.08	<b>50.0</b>	0	50.0	38.10	27.27	<b>64.71</b>
Outer suburbs	40.0	43.59	18.75	16.67	31.25	28.57	<b>72.73</b>	17.65
Inner suburbs	5.0	15.38	18.75	<b>50.0</b>	18.75	14.28	0	5.88
Paris	25.0	17.95	12.5	33.33	0	19.05	0	11.76

613

## 614 4.2. Results from the diary study

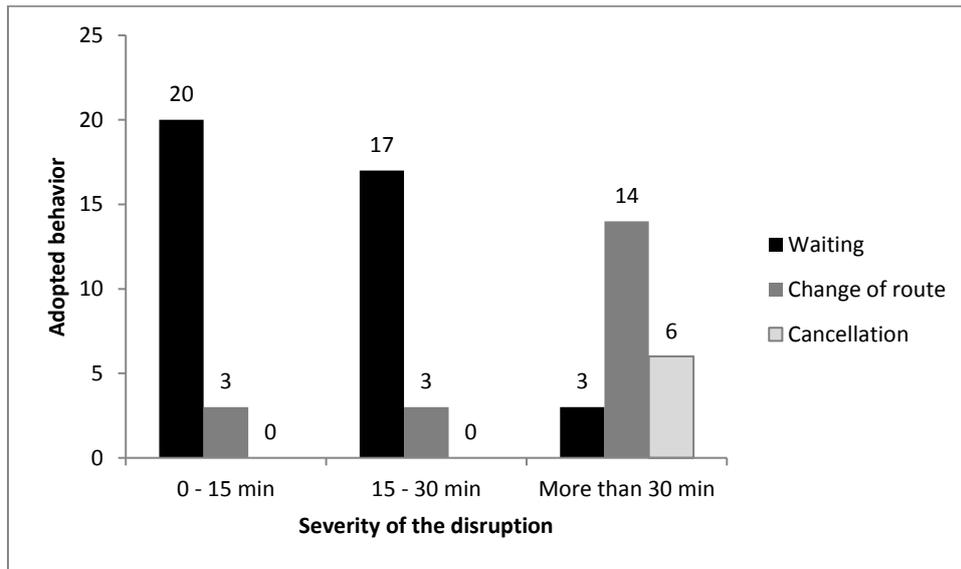
615 The 38 passengers who took part in the second phase reported 80 disruptions (between one  
616 and seven each). We decided not to analyze disruptions in which the train stopped between  
617 stations, as this limited the passengers' available options to waiting. We therefore decided to  
618 analyze 67 reported events. Certain events were reported by 7 to 10 users; for example:

- 619 • a signaling malfunction that occurred on line N on March 26, 2015, from 4:30 to 11:40 AM  
620 with many train cancellations (10 users)
- 621 • a suicide that interrupted service for a few hours during the evening peak hours on line C  
622 on March 27, 2015 (7 users)
- 623 • track problems with an important slow of circulation and a reduction of the number of  
624 trains on line C in the evening on March 26, 2015 (8 users)
- 625 • a switch failure that occurred on the three studied lines from the beginning of the evening  
626 peak hours until 9 PM on March 25, 2015, with important delays and train cancellations  
627 (8 users)
- 628 • a catenary break that caused delays on line N and interrupted trains' circulation on line C  
629 on April 3, 2015 (7 users)

630 Because of the great variety of studied disruptions (causes, location, duration), we choose to  
631 analyze suburban train users' reactions depending on the severity of the disruption. The  
632 severity is estimated by two distinct indicators: waiting time estimated by users who changed  
633 strategy (*In your opinion, how much time would you have waited if you had not made this*  
634 *choice?*) and real waiting time reported by those who decided to wait (*How long did you*

635 *wait?*). The result is 3 categories of severity: delays of less than 15 min (23 cases), delays  
636 from 15 to 30 min (20 cases) and delays of more than 30 min (23 cases).

637 First, the results of the diary study were processed by crossing the passengers' adopted  
638 behavior and the severity of the disruption. To facilitate analysis, all options that involved  
639 leaving the public transport network were recoded as a cancellation (destination change,  
640 cancellation of trip, exclusive use of a car, use of a two-wheeler, or walking to the  
641 destination).



642

643 **Fig. 3. Adopted behavior according to estimated or actual waiting time**

644 The results (see Fig. 3) show that passengers prefer to wait in the case of disruptions that  
645 would make them wait less than 30 min. However, for delays over 30 min, cancellation  
646 appears as an option, and route change becomes the decision made by the majority.

647 However, not all respondents behaved in the same way. We then compared situations in  
648 which some individuals behaved differently from others at a given level of disruption severity.  
649 For example, we compared the three situations/passengers who chose to change routes in  
650 response to a minor disruption with the twenty who choose to wait (see Fig. 3). Conducting  
651 these comparisons enabled us to glimpse the possible impact of four factors on the behavior  
652 adopted by individuals: position on the line, time constraints, the step of the trip when the  
653 information was received (pre-trip or en route) and users' evaluation of the situation. More  
654 specifically, we observed that living at the end of a line could make it more difficult to change  
655 routes and encourage individuals to wait or cancel their journey. We have also seen that time  
656 constraints can have an impact. Individuals with time constraints behave in a more  
657 stereotyped manner and change their routes; other individuals seem to make more varied  
658 choices in accordance with their desires. We also observed that the information received had

659 an impact. In the event of a minor disruption, receiving pertinent information when at home  
 660 encourages individuals to wait before leaving for the station. In the event of a more serious  
 661 disruption, receiving information at home encourages cancellation. Lastly, individuals'  
 662 assessment of the severity of the situation may affect their decision. If they do not think they  
 663 will have to wait a long time, they will use this solution.

664 Eight users filled in several diary entries in which they described different reactions (Table  
 665 11).

666 **Table 11. Characteristics and behaviors of respondents with multiple diary entries (names are fictitious)**

Respondents	Number of diary entries	Content of diary entries
Julie, 49, employee, line N	6	2 waiting: less than 15 min delay, disruption known at home 4 route changes: more than 30 min delay, disruption known at the train station
Joshua, 21, student, lines N and C	4	3 waiting: less than 30 min delay 1 mode change (for car): more than 30 min delay
Christopher, 39, manager, lines N and C	4	1 waiting: delay between 15 and 30 min 1 route change: delay between 15 and 30 min 2 mode changes (car): more than 30 min delay, high temporal constraints, disruption known at home
Paul, 45, technician, lines N and C	5	3 waiting: less than 30 min delay 1 route change: more than 30 min delay, return trip 1 mode change (car): more than 30 min delay, outbound trip, high temporal constraints
Thomas, 22, manager, line N	4	3 waiting: outbound trip 1 route change: return trip
Lisa, 49, employee, line C	7	3 waiting: return trip 3 route changes: more than 30 min delay, return trip 1 teleworking: more than 30 min delay, outbound trip
Melissa, 39, intermediate profession, lines N and C	2	1 waiting: less than 15 min delay 1 route change: more than 15 min delay
Jessica, 19, student, line C	2	1 waiting: less than 30 min delay 1 route change: more than 30 min delay

667  
 668 We observe that the severity of the disruption has a major impact on the chosen behavior for  
 669 seven cases. The severity of disruptions that result in waiting appears to differ from the  
 670 severity of disruptions that lead to changes, switching to a car or cancelling the trip.  
 671 However, the severity of the disruption is not the only determinant; the threshold above which  
 672 waiting is no longer the preferred option varies between 20 and 40 min depending on the  
 673 individuals and the situations described. Different situational variables seem to influence the  
 674 choices of users at a less distinct level; these variables include time constraints, the direction  
 675 of the trip (outbound or return), and the moment at which the disruption is communicated.  
 676 These factors are observed for only two or three users. Weak time constraints can  
 677 encourage waiting, while strong ones can lead individuals to favor other strategies, especially  
 678 car use. It is likely that the direction of the trip is linked to the behavior of three respondents.  
 679 When at home, suburban train users are more likely to cancel their trip or to use their car.  
 680 Lastly, this comparison suggests an influence of the time at which users receive information  
 681 on their behavior (for two users), as we observed in the previous section. Receiving  
 682 information when en-route (even if at the departure station) encourages individuals to change

683 routes, while if they receive it pre-trip, it encourages them to wait, use a car, or cancel their  
684 trip.

685 These results should be considered invitations for further empirical research. Indeed, the use  
686 of situations of real disruptions encountered by individuals with different characteristics and  
687 in different situations does not allow comparisons with large samples. If only two users  
688 describe an effect of time constraints, this does not necessarily mean that there is no effect  
689 for the others; rather, it means that the time constraints were at the same level for the others  
690 in the cases they reported.

## 691 **5. Discussion**

692 Despite the importance of this topic, little research has focused on the behavior of suburban  
693 train passengers when faced with an unexpected disruption (Lin & al., 2016). Most of the  
694 studies in this area focus on the complete withdrawal of public transport; planned, long-term  
695 disruptions; transport users in general; or motorists' behavior. Our study has highlighted  
696 possible determinants of the short-term behaviors of suburban train users in unplanned  
697 short-term disruptive situations caused by technical or human factors. This type of disruption  
698 is the one most commonly encountered by suburban train users in the Ile-de-France Region.  
699 With regard to the method, we used a two-step RP survey: a questionnaire about the last  
700 major disruption encountered and a diary study about all disruptions encountered by a  
701 respondent during a two-week period. While diary studies have been used to understand  
702 mobility behavior, they have not been used to understand behavioral adaptation to  
703 disruptions. Only the diary study by Bonsall and Dunkerley (1997) examined the impact of  
704 information about a strike, even though the study had another initial aim. Using a diary study,  
705 we performed an in-depth analysis of the link between a clearly described disruption and a  
706 particular user in a particular situation. We also identified the types of strategies adopted as a  
707 reaction to major or less severe disruptions in order to create a realistic passenger flow  
708 model. After a short discussion regarding behavioral choices in case of disruption, the first  
709 part of the next section discusses factors influencing suburban train passengers' behavior  
710 when faced with a disruption. The second part reflects on the identified behavioral profiles. In  
711 the final part, limitations of the study are discussed.

### 712 **5.1 Behavioral choice in case of severe disruption**

713 In our study, suburban train users considered route changes as the first choice when faced  
714 with a severe disruption (between 70 and 77% users made this choice, depending on the  
715 direction of the trip). Lin & al. (2018) found a similar result, but a smaller portion of their  
716 sample (39%) made this choice. Van Exel and Rietveld (2001) obtained a very different

717 result, with the majority of commuters leaving home as usual and using the disrupted mode.  
718 In the case of a pre-announced strike, the main behavior was mode change. For example, in  
719 the context of train strikes, van Exel & Rietveld (2009) found a 24% mode change to cars. In  
720 our situation of a disruption on passengers' usual line, the rate of change to a car was  
721 between 13 and 20%, depending on the direction of the trip. On complete public transport  
722 withdrawal, Nguyen-Phuoc et al. (2018b) found a 51.7% mode change to a car as a driver. In  
723 the case of weather or natural events, cancellation, route change and travel time changes  
724 were mainly observed (Zhu & Levinson, 2012; Marsden & al., 2016). It seems that depending  
725 on the type, severity, magnitude, and duration of a disruption, the behavior of transport users  
726 changes. It is also very likely that the location of the place where the disruption occurs  
727 impacts the available solutions and the choices that are made (Marsden & al., 2016).

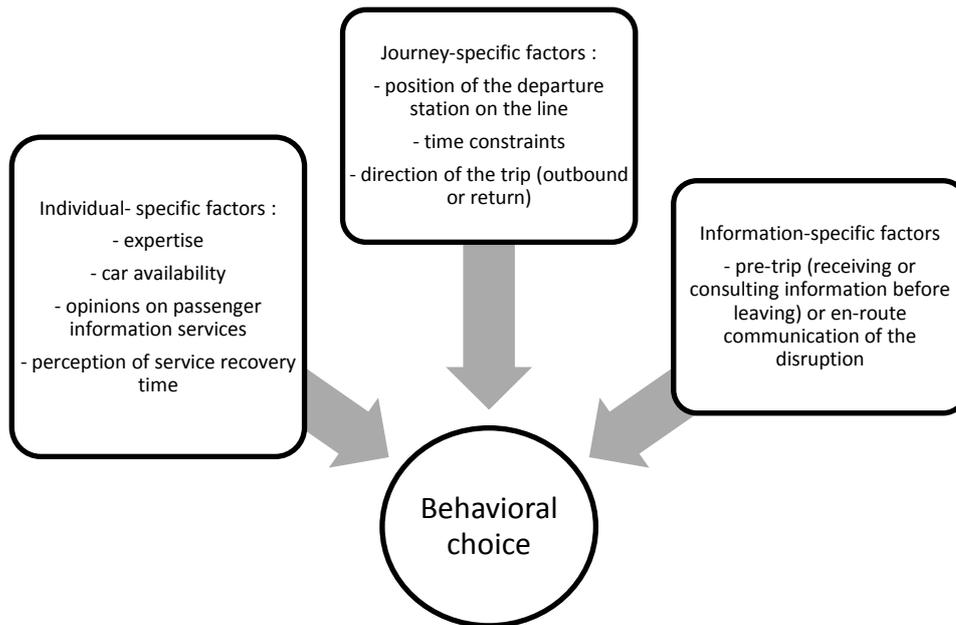
728 Our study also shows what could be considered an acceptable route alternative by suburban  
729 train users by focusing on real choices: an average increase of 25% of the trip duration and  
730 the use of different modes, mostly a change in the origin or destination stations, implying the  
731 use of walk or car to reach the new station or walking to reach the destination. However, the  
732 number of transfers between two modes of public transport or two lines of the same public  
733 transport mode seems to remain relatively close. This could indicate that users prefer not to  
734 complicate their trips. Such precise information is scarcely available in the literature. Only the  
735 diary study by Bonsall and Dunkerley (1997) shows an increase of bus use during subway  
736 strikes.

## 737 **5.2 Factors influencing behavior**

738 Even if the severity of a disruption seems to be the greatest contributing factor to the  
739 selection of alternatives, the findings show that passenger shifts are influenced not by one  
740 factor alone but by a combination of linked factors. Fig. 4 proposes a summary of the  
741 statistically significant factors influencing suburban trains users' behavior in the event of a  
742 disruption (from section 4.1.2).

743 **Fig. 4. Factors influencing behavior in the event of a disruption**

744



745

746 Generally speaking, the study confirms the role of the determinants identified by previous  
 747 studies on driver behavior. More precisely, the results concerning the modalities of these  
 748 determinants and the associated behaviors tend to be consistent with previous findings. In  
 749 the paragraphs below, we consider various determinants: individual-specific factors  
 750 (expertise, car availability, opinions on passenger information, passengers' estimation of their  
 751 waiting time), journey-specific factors (available transport services, time constraints), and  
 752 information-specific factors (pre-trip or en-route communication of the disruption). We also  
 753 describe the determinants identified by other researchers for which we observe no effect on  
 754 behavior.

755 With regard to expertise, our research shows passengers with a good understanding of  
 756 networks and experience with the routes used are more willing to wait than novice users.  
 757 This result is linked with results obtained on drivers. We know, for example, that habit is  
 758 important in the inhibition of active decision-making (Van der Horst, 2004) and that  
 759 individuals with a certain level of knowledge about routes that are familiar to them will be  
 760 more reluctant to use unfamiliar parts of the network (Chorus & al., 2006b). This result could  
 761 also be associated with commuters' inertia, as highlighted by van Excel and Rietveld (2001).  
 762 Some other hypotheses can be put forward and confirmed by future research. First, perhaps  
 763 the most experienced passengers know that it is better to wait for a return to normality than  
 764 change to an overloaded alternative route. Second, the routine of daily trips can lead to a  
 765 form of resignation that discourages users from making an effort to use another solution.  
 766 Lastly, experienced passengers could have developed habits during waiting time that make  
 767 this time more productive. A new study could clarify what waiting entails and consider the

768 possibility to delay the start of a trip, which could be a solution used by experts. Existing  
769 studies about major disruptions propose this solution in possible answers (Marsden & al.,  
770 2016).

771 We have also shown that having access to a car encourages passengers to use this mode in  
772 the event of a major disruption (Khattan & Bai, 2018; Nguyen-Phuoc & al., 2018a). Car  
773 availability is linked with respondents' age and socio-occupational group. Thus, observable  
774 differences in behavior according to sociodemographic determinants may be mediated by the  
775 availability or unavailability of a car.

776 Regarding opinions, we have shown a possible link between users' opinions about  
777 passenger information and the behavior they adopt. More specifically, individuals with an  
778 opinion that is in favor of the rapidity, completeness, usability, systematic nature, and  
779 reliability of information are likely to change their route in the event of a major disruption. We  
780 have not found another study in the literature that tests the impact of this opinion on  
781 behavior. We therefore formulate a hypothesis that should be tested by further research. It is  
782 possible that a high level of confidence in information encourages a clear evaluation of the  
783 situation, low uncertainty and, consequently, proactive decisions.

784 The diary study allowed us to focus in detail, from a limited number of real cases, on the link  
785 between disruptive situations, the passengers involved and their behavior. We were  
786 particularly interested not in the link between the real characteristics of the disruption and  
787 user choices but in the link between the expected waiting time and choices. If users estimate  
788 that their waiting time will exceed 30 minutes, they will implement a strategy not to wait on  
789 the spot. Future research could focus on how this assessment works. Moreover, we have  
790 shown that this threshold is quite different between individuals.

791 Concerning the journey-specific factors, the characteristics of the transport system of the  
792 place in which individuals find themselves when a disruption occurs has an effect on their  
793 decisions. The ease or difficulty with which users can change routes affects their behaviors  
794 (Khattan & Bai, 2018). This was shown by both the RP study and the diary study. When it is  
795 difficult to change routes, i.e., when there are few opportunities and those that exist have  
796 unacceptable characteristics (extremely long journey time, complexity), other solutions, such  
797 as asking for a ride, cancelling the trip or waiting, are preferred. **This is especially the case**  
798 **when passengers live in remote outer suburbs where the transport supply is relatively low.** In  
799 this situation, too, specific habits have been highlighted with regard to traffic information.  
800 Users who have a tendency to wait during major disruptions because they have no other  
801 solution are reticent with regard to traffic information, seeking it less than others (Peirce &  
802 Lappin, 2004). Indeed, information is useless for them. Then, some of our results indicate

803 that time constraints lead individuals to modify their behaviors, but the obtained results are  
804 not sufficient to draw conclusions. Additional studies are needed in this area.

805 Concerning the information-specific factors, learning about the occurrence of a disruption  
806 pre-trip or en-route may have a significant impact on users' behavior (Lin & al., 2016). This  
807 was confirmed by the questionnaire and supported by the diary study. Individuals who  
808 change to a car tend to subscribe to notifications in order to learn about major disruptions  
809 before going to the station. For these individuals, it is very helpful to automatically receive  
810 information in real time before leaving for the station and removing car travel from the set of  
811 alternatives (Polak & Jones, 1993). The diary study suggests that user behavior varies  
812 depending on the step of the trip when information is received. This variation is confirmed by  
813 inter-individual and intra-individual comparisons and in the literature (Lin & al., 2016).

814 Finally, some of the possible determinants we have tested do not appear to affect the  
815 behavior of passengers in disruptive situations. This applies, in particular, to passengers'  
816 personality. In contrast to what was shown by Shiftan, Bekhor and Albert (2011) regarding  
817 the role of sensation seeking on the decisions made by motorists, our study detected no  
818 such link. In addition, we found no impact for gender, which was identified as an explanatory  
819 factor by Zhang, Yun and Yang (2012), and the impact of socio-occupational group was fairly  
820 limited.

### 821 **5.3 Behavioral profiles**

822 Based on clustering, we were able to link behavioral patterns, namely, respondents'  
823 behavioral solutions in past situations of major disruptions on the outbound and return  
824 journey, with explanatory variables identified by bivariate analyses. We identified eight user  
825 clusters that became behavioral profiles in the simulation tool. Due to the shortcomings of  
826 our sample, the distribution of these classes cannot be considered an accurate  
827 representation of the entire population using the studied lines. We nevertheless found some  
828 interesting information regarding the different ranges of solutions of the clusters of suburban  
829 train passengers. In particular, these classes exhibit marked adaptive behaviors with regard  
830 to disruptions. A varying number of characteristics with regard to sociodemographic and  
831 geographical factors, vehicle ownership, and individuals' relationship with information are  
832 associated with each of these classes. The sample of suburban train passengers is divided  
833 into three major clusters and five minor clusters. The major classes contain individuals who  
834 change their routes, teleworkers (who have the option of not going to work) and motor  
835 vehicle owners (who have access to a car). The minor classes bring together those  
836 passengers we called constrained because they have poor transport service for their  
837 commute, those who are passive on their return journey, those who are flexible, those who

838 choose to be passengers in other vehicles and those who are not obligated to reach their  
839 destination on the outbound journey. Regarding users who are “passive on their return  
840 journey”, we predict they are individuals who have no constraints with regard to their time of  
841 arrival at home, particularly in terms of family duties. They are therefore free to take their  
842 time in the evening, although they have to arrive at work on time in the morning.  
843 Unfortunately, we did not ask any questions about household composition to check this  
844 notion. The “leisure users” group seems to be heterogeneous. It is the smallest group in our  
845 sample. This is the only group that changes their destination on outbound trips. One  
846 hypothesis is that this group is composed of real leisure users and desk-sharers. As we  
847 asked no questions about multiple places to work or study, we were not able to better qualify  
848 this cluster.

#### 849 **5.4 Limitations of the study**

850 We end this discussion by describing the main limitations of our study, which are mainly  
851 methodological. Due to a lack of data that would have enabled us to easily identify the users  
852 of the studied lines, we were unable to contact more appropriate individuals for our study.  
853 This lack of respondents meant we were unable to construct a representative sample that  
854 would enable us to make generalizations from the percentages of the profiles we identified in  
855 the population using lines N, U and C. Furthermore, the lack of participants, particularly in the  
856 case of the diary study, meant we were unable to perform all the comparisons we would  
857 have liked to, particularly by highlighting the relation between the trip purpose and the  
858 passenger’s behavior. Several studies have considered how the purpose of the trip affects  
859 passengers’ choice behavior, producing strong evidence (Marsden & al., 2016; Nguyen-  
860 Phuoc & al., 2018a; van Exel & Rietveld, 2001). Furthermore, we chose to focus on a limited  
861 number of Transilien lines. Thus, it is impossible for us to know whether the findings are  
862 transferable to all suburban train users. Thus, the chosen mode of contact induced selection  
863 bias since people far from new technologies were not interviewed. Finally, to provide  
864 information to simulate passenger flows, the selected scale led us to neglect some micro  
865 factors implied in behavioral choices, such as the availability of car parks and congestion.  
866 We will consider different solutions for a future study with more participants and will cross our  
867 results with a big-data analysis.

#### 868 **6. Conclusion**

869 This study contributes to research on the behavior of suburban train passengers in a  
870 disruptive situation from three points of view: theoretical, methodological and applicative.  
871 From the theoretical standpoint, this research improves our understanding of the behavior of  
872 suburban train passengers who are faced with disruptions and the mechanisms behind these

873 behaviors. The determinants of behavior we have identified are linked with the individual  
874 involved in the disrupted situation, with the journey that is made and with the information  
875 given. From the methodological standpoint, we have studied the behavior of users in  
876 situations that are as close as possible to reality by implementing a specific repeated-  
877 measures procedure based on a travel diary. To obtain more data, we also exploited  
878 questions that were more disconnected from real disruptions. We thus mixed two RP  
879 methods (Shiftan, Bekhor & Albert, 2011). From the application standpoint, this research,  
880 despite its preliminary nature, allowed us to integrate passenger behaviors with multi-agent  
881 software that simulates a multimodal transport network (Tschirhart, Adélé, Bauguion &  
882 Tréfond, 2016).

883 This work also provides some direction for future research. We feel that studies should  
884 exploit the first questionnaire to understand the behaviors individuals adopt during  
885 disruptions by varying the severity of disruptions. With this questionnaire, we only addressed  
886 major disruptions. Thus, we performed a second survey whose results will be published in  
887 the near future. We also feel that greater attention should be given to the role played by  
888 information and its interpretation in the decision-making process. This will be covered by a  
889 new project that will make use of more qualitative methods, such as explanatory interviews  
890 (Vermersch, 1994).

891 For human sciences, producing results for modeling represented a challenge and obliged us  
892 to operate at a larger scale than usual. It would be valuable to conduct other multidisciplinary  
893 projects, as these have a greater capacity to advance research on the modeling of behaviors  
894 in transport systems.

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