Exploring association between perceived importance of travel/traffic information and travel behaviour in natural disasters: a case study of the 2011 Brisbane floods

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Abstract: A sound understanding of travellers’ behavioural changes and adaptation when facing a natural disaster is a key factor in efficiently and effectively managing transport networks at such times. This study specifically investigates the importance of travel/traffic information and its impact on travel behaviour during natural disasters. Using the 2011 Brisbane flood as a case study, survey respondents’ perceptions of the importance of travel/traffic information before, during, and after the flood were modelled using random-effects ordered logit.

A hysteresis phenomenon was observed: respondents’ perceptions of the importance of travel/traffic information increased during the flood, and although its perceived importance decreased after the flood, it did not return to the pre-flood level. Results also reveal that socio-demographic features (such as gender and age) have a significant impact on respondents’ perceptions of the importance of travel/traffic information. The roles of travel time and safety in a respondent’s trip planning are also significantly correlated to their perception of the importance of this information.

The analysis further shows that during the flood, respondents generally thought that travel/traffic information was important, and adjusted their travel plans according to information received. When controlling for other factors, the estimated odds of changing routes and cancelling trips for a respondent who thought that travel/traffic information was important, are respectively about three times and seven times the estimated odds for a respondent who thought that travel/traffic information was not important. In contrast, after the flood, the influence of travel/traffic information on respondents’ travel behaviour diminishes. Finally, the analysis shows no evidence of the influence of travel/traffic information’s on respondents’ travel mode; this indicates that inducing travel mode change is a challenging task.

Keywords: Travel information; traffic information; travel behaviour; adverse weather; natural disaster; random-effects ordered logit

1. Introduction

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Information plays a vital role in everyday trip-making decisions and changes. Travellers use such information to reduce their travel time, cost, and other undesirable factors by adjusting their choice of departure time, route and mode. In extreme events, the role of information is crucial because travellers often face great uncertainties during such events, and safety (rather than comfort or a reduction in travel time or cost) becomes their primary concern.

Travel/traffic information can be broadly categorised into two classes: en route information and pre-trip information. En route information is mostly concerned with regulatory traffic information (e.g., speed limit, lane closure or toll) and with downstream traffic conditions (e.g., a major incident, congestion or road closure). En route traffic information allows drivers to control their speed, lane change and, in some circumstances, route change. These are instances of real time travel information that allow traffic engineers to manage traffic operation to provide significant benefits in improving traffic network performance (For more information on en route traffic information, see Ben-Akiva et al., 1991; Pan and Khattak, 2008). In contrast, pre-trip information is provided for, or accessed by travellers prior to their trips through media such as newspapers, television, radio, telephone, websites, and smart phone apps, and can influence the trip maker to change most aspects of their journey (including departure time, route, mode, or destination), or even to cancel their trip (Jou, 2001; Mannering et al., 1994).

A sound understanding of travellers’ behavioural changes and adaptation when facing a natural disaster is a key factor in efficiently and effectively managing transport networks at such times. Travellers are likely to make judgements about these changes and adaptations based on the information they collect from different sources. In normal operating conditions, travellers’ day-to-day travel experiences of network conditions are the primary source of their information. During a natural disaster, however, travel conditions can change and, in most cases, people affected by the disaster do not rely on their previous travel experiences; rather, they turn to other sources of information such as television, radio, newspapers, the internet and word of mouth.

Information plays a significant role during an extreme situation by providing those affected with an understanding of the overall situation and a sense of confidence in their decision making. Although the use of travel/traffic information to influence travel behaviour is widely studied and significant progresses have been made (see Literature Review), most of these studies focused on hurricane evacuation and very few studies were based on floods that did not cause a large-scale evacuation. Furthermore, no studies explicitly measured perceived importance of information and its linkage to behavioural changes during a natural disaster. This study fills this research gap by qualitatively and quantitatively analysing perceptions of the importance of travel/traffic information and its potential impact on travel behaviour during the 2011 Brisbane floods.

The state of Queensland (Australia) experienced a series of floods from December 2010-January 2011 – the second largest flood event in the past 100 years. About three quarters of the state was affected, and more than 200 000 people were affected. The flood also had a major impact on transport facilities: Over 9000 km of roadway and over 3000 km of
Queensland rail track across the state were affected (Queensland Transport and Main Roads, 2012); ferry services on the Brisbane River were shut down completely from January 10, 2011 and partially resumed on February 14, 2011. Public transport services in South East Queensland were suspended for two days at the height of the flood event (Brown et al., 2011), and this disrupted the travel behaviour of residents in the flood-affected regions.

Brisbane city region was one of the areas in Queensland that were severely hit by the flood. Before the flood, Brisbane City Council (BCC) undertook a series of initiatives to raise awareness in the community regarding the increased risk of flooding, including the implementation of an Early Warning Alert Service. However, very few residents registered for the service. This changed during the flood as many residents sought the latest information on the flooding and traffic situation. Public information about the flooding was provided and accessed through a variety of channels including television, radio, print media, newsletters, the council’s Call Centre, website, and social media (Brisbane City Council, 2011). This provided an excellent opportunity for investigating two critical but rarely studied issues: residents’ perceptions of the importance of travel/traffic information when facing great risks and uncertainties associated with a natural disaster, and the potential impact of such perceptions on their travel behaviour.

Taking the 2011 Brisbane flood as a case study, therefore, this research focuses on residents’ various information sources and needs, and their travel behaviour adjustments at different stages of the flood, and scrutinizes the relationships between perceptions of the importance of travel/traffic information, changes in travel mode and route, and socio-demographics factors. Insights gained from the study can be used to design more effective travel information systems and to develop more efficient traffic management strategies, two critical components of disaster response systems. Note that when used hereafter in this paper, ‘information’ refers to travel/traffic information, unless otherwise stated.

The remainder of the paper is organised as follows. Section 2 reviews previous related studies; Section 3 provides details of the survey data collection process; Section 4 qualitatively analyses respondents’ information sources and their perceptions of the importance of information at the various stages of the flood; Section 5 models changes in respondents’ perceptions of the importance of information, and its linkage to their mode and route choices; and Section 6 concludes the paper by summarizing major findings.

2. Literature Review

Natural disasters often force travellers to immediately adjust their travel behaviours in and around the disaster-affected areas or to evacuate the disaster area in worst cases (Homberger, 1990; Giuliano and Golob, 1998). In the situations where a large-scale evacuation is not warranted, travel behaviour adjustments are mostly limited to changes in trip schedule and route. Based on 70 case studies of road capacity reduction, Cairns et al. (2002) conclude that in response to a network degradation, people change mode, consolidate trips for different purposes, and visit alternative destinations; however, the most universal adjustment is the changing of route and departure times. Similar findings are observed in Ye et al. (2012), Zhu...
et al. (2010), Tilahun and Levinson (2009), and Giuliano and Golob (1998). Two opposite
situations were observed in the aftermath of the Northridge Earthquake, Southern California
in 1994. Travellers responded differently in each of the four damaged corridors. When
alternative streets parallel to the damaged freeway were available, most travellers responded
to the disruption by adjusting routes and travel time schedules. In contrast, where parallel
roadways were limited there were substantial shifts to commuter trains and a sharp increase
in transit ridership was observed (Wesemann et al., 1996; Giuliano and Golob, 1998). Note
that evacuation modelling is a frequently studied topic in the literature (Alsnih et al., 2005;
Fu et al., 2007; Lindell and Prater, 2007; Pel et al., 2010; Pel et al., 2012; Dixit et al., 2012),
and is beyond the scope of this paper. For a detail review on evacuation transport modelling
see Murray-Tuite and Wolshon (2013).

Information plays a vital role in travel decisions, particularly when travellers are facing high
uncertainties during a natural disaster and subsequent network disruptions. Travel/traffic
information can be categorized into two groups: pre-trip information and en route
information. Pre-trip information is capable of influencing the choice of departure time
choice, mode, travel route, or even cancellation of the trip; whereas en-route information is
mostly used to ensure smooth traffic flow by providing information about alternative routes,
congestion etc. Similar to pre-tip information use, an increase in en-route information use is
observed in the past decade due to improvement in Advanced Traveller Information System
(ATIS), in-vehicle technology and digital media (Robinson and Khattak, 2010).

Prater et al. (2000) examined information sources during Hurricane Bret in 1999. Television
networks were found to be the most important source of information, followed by local radio
broadcasts. Local newspaper and internet were the least important information sources.
Interestingly the residents valued information gathered from friends and family more than
that from newspaper or the Internet. However, the order of information could be different for
different incident types. For example, in a survey of travel behaviour in the aftermath of the I-
35W Bridge collapse in Minneapolis, Tilahun and Levinson (2009) and Zhu et al. (2010)
observe a different order of relying on information source. Friends and family was reported
as the primary source of information followed by media (such as TV, radio, and internet). For
respondents who were not affected by the collapse, the order was reversed: their primary
information source of was media. Robinson and Khattak (2010) reported five information
sources commonly used while driving: Radio, ATIS, mobile phone, Internet and GPS. In
their survey, radio was the most prominent means for en-route travel/traffic information
followed by ATIS. Internet and GPS were least used.

Risk communication specialists are often baffled by the seemingly common phenomenon of
resistance to risk messages, especially when an evacuation is warned (Drabek, 1999;
Fischhoff, 2006; Taylor et al., 2009). Fischhoff (2006) described six possible explanations:
failure to act sensibly; failure to realize risk messages being directed at them; failure to
receive risk information at all; lack of trust on the messages; lack of information access; and
communicators’ failure to provide useful information. Furthermore, the wording and content
of evacuation message, person delivering the message, and distribution medium, can
influence the evacuation outcome (Murray-Tuite and Wolshon, 2013). After the deadly
Hurricane Katrina, Taylor et al. (2009) observed that, although the access to and understanding information mattered, the decision to evacuate was clearly a social one. Those who chose not to leave the danger area were most likely influenced by the decisions of people around them (e.g., families, friends, neighbours, and co-workers). Thus, the way evacuation messages are delivered should also be adjusted accordingly to be more effective.

Meanwhile, several studies investigated information’s influence on route choice (e.g. Dow and Cutter, 2002; Murray-Tuite et al., 2012; Robinson and Khattak, 2010). Prater et al. (2000) observed that 69% of the respondents use the most logical route based on their experience during the evacuation for Hurricane Bret. Similar finding is also reported in Murray-Tuite et al. (2012) for Hurricane Katrina in 2005, where the majority of the evacuees selected their familiar routes and ignored the recommended route. Dow and Cutter (2002) found strong preferences for interstate routes even when the evacuees had easy access to alternative routes. From a stated preference survey on Hurricane evacuations in the Hampton Roads region of Virginia, Robinson and Khattak (2010) reported that evacuees’ would be highly motivated to use an alternative route when longer than expected delays are observed on the intended route and when detail information on congestion is provided to the drivers. Sadri et al. (2013) found that socioeconomic characteristics such as income, age and number of children influence routing decisions. Pel et al. (2010) observed that, when travellers are not well informed and are unfamiliar with the network, the network is underutilized. Robinson and Khattak (2012) show that with information provided by ATIS or radio, the percentage of drivers expecting to divert ranged from 32.5% to 93.8%. Experience can also play an important role in evacuees’ route choice behaviour (Kang et al., 2007).

In summary, many studies investigated information use and their potential impact on travel decisions during natural disasters, and significant progresses have been made. However, most of these studies focused on hurricane evacuation and very few studies were based on floods that did not cause a large-scale evacuation. Furthermore, although the importance of people’s perception on travel information was hinted in some studies (e.g., Taylor et al., 2009), no studies explicitly measured perceived importance of information and its linkage to behavioural changes during a natural disaster. This study fills these gaps.

3. The Survey

To observe the impact of the 2011 Brisbane flood on travel behaviour, a detailed web-based survey was conducted between 15 March and 26 April 2013. Respondents whose travel was affected by the flood were asked about their travel experiences before, during, and after the event. To ensure that respondents who used different transport modes were recruited, invitations to participate in the survey were distributed at bus stations, train stations, ferry stations and bike paths in the Brisbane city area. The questionnaire contained 4 sections: questions about demographics, questions related to travel before and during the flood, and questions related to respondents’ current travel situation. To increase the response rate, an AU$10 gift card was offered as an incentive to complete and submit the survey.
Before the final survey, two pilot surveys were conducted to refine the questionnaire and to strengthen its validity and readability. Twenty participants were randomly intercepted and asked to participate in the first pilot survey. At the end of this survey, each participant was asked to provide specific comments on the questions. The questions were then revised based on this feedback, and translated to the web-based platform. A second pilot survey was then implemented by emailing invitations to 15 students and staff at Queensland University of Technology (QUT) to test the online platform. The online survey platform was subsequently adjusted according to the comments from this second pilot survey.

Besides these strategies discussed above, to further increase the quality of our survey data and to minimize potential memory bias because of the two years gap between the flood and the survey, before respondents were allowed to answer questions, a description of the flood with some vivid photos taken during the flood was presented to them, to refresh their memories. During these two pilot surveys, no any issues related to memory bias were raised by participants, which is not surprising because it naturally takes a long time for people in the region to forget the enormous damage to the transport network caused by this large scale flood (see Section 1) and no large-scale interruptions have occurred to the transport systems in Southeast Queensland over the last two years since the 2011 flood.

The final survey was undertaken by 550 respondents who were to some extent affected by the flood. Among these, 126 were so severely affected that they had to cancel their usual daily trips during the whole flood period; thus, they were unable to respond to questions about their travel behaviour during the flood event. The average age of the respondents in this survey was 40.7; this compares with the 2011 35.1 median age of residents in the Brisbane area, as reported by Australian Bureau of Statistics (ABS) in 2012. Of the respondents, 370 (57%) were female, and 180 (33%) were male. According to the ABS, the gender percentages of greater Brisbane residents are almost equal: 50.3% female, and 49.7% male. The study sample was not an exact representation of the Brisbane population, as it only included flood-affected residents. Some general characteristics of the study’s respondents are presented in Table 1. And main variables used in this study are summarized in Table 2.

One question asked respondents directly about the impact of the 2011 Brisbane flood on their daily travel behaviour. Besides route changes and mode changes, about 67% had to cancel their daily trip for at least one day.

Note that although this paper concentrates on association between information usage and behavioural changes, information on many other important aspects relevant to the flood’s impact on respondents’ travel has also been collected, such as departure and arrival times, home and destination suburbs and postcodes, how and to what extent respondents were affected by the flood, a series of questions to bus riders, and a series of questions on respondents’ attitudes/perceptions towards different transport modes. These questions provide opportunities to study many other important issues related to the travel management during a natural disaster.
<table>
<thead>
<tr>
<th>Category</th>
<th>Counts</th>
<th>Histogram with percentage</th>
<th>Study (%)</th>
<th>Brisbane (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Gender</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Female</td>
<td>370</td>
<td>![Female Bar Chart]</td>
<td>57%</td>
<td>50.1%</td>
</tr>
<tr>
<td>Male</td>
<td>180</td>
<td>![Male Bar Chart]</td>
<td>33%</td>
<td>49.9%</td>
</tr>
<tr>
<td><strong>Age (16 is the minimum age for a person to legally drive a car in Queensland)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>16-17</td>
<td>3</td>
<td>![16-17 Bar Chart]</td>
<td>1%</td>
<td></td>
</tr>
<tr>
<td>18-30</td>
<td>133</td>
<td>![18-30 Bar Chart]</td>
<td>24%</td>
<td>26%</td>
</tr>
<tr>
<td>31-40</td>
<td>173</td>
<td>![31-40 Bar Chart]</td>
<td>31%</td>
<td>19%</td>
</tr>
<tr>
<td>41-50</td>
<td>74</td>
<td>![41-50 Bar Chart]</td>
<td>13%</td>
<td>14%</td>
</tr>
<tr>
<td>51-60</td>
<td>97</td>
<td>![51-60 Bar Chart]</td>
<td>18%</td>
<td>11%</td>
</tr>
<tr>
<td>61 or more</td>
<td>69</td>
<td>![61 or more Bar Chart]</td>
<td>13%</td>
<td>9%</td>
</tr>
<tr>
<td>No answer (omitted from modelling)</td>
<td>1</td>
<td>![No answer Bar Chart]</td>
<td>0%</td>
<td></td>
</tr>
<tr>
<td><strong>Highest educational qualification (Education)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Grade 10 or below</td>
<td>44</td>
<td>![Grade 10 or below Bar Chart]</td>
<td>8%</td>
<td></td>
</tr>
<tr>
<td>Grade 11</td>
<td>16</td>
<td>![Grade 11 Bar Chart]</td>
<td>3%</td>
<td></td>
</tr>
<tr>
<td>Grade 12/School Certificate</td>
<td>102</td>
<td>![Grade 12/School Certificate Bar Chart]</td>
<td>19%</td>
<td>13%</td>
</tr>
<tr>
<td>Technical qualification/certificate</td>
<td>149</td>
<td>![Technical qualification/certificate Bar Chart]</td>
<td>27%</td>
<td>6%</td>
</tr>
<tr>
<td>Undergraduate university degree</td>
<td>137</td>
<td>![Undergraduate university degree Bar Chart]</td>
<td>25%</td>
<td>32%</td>
</tr>
<tr>
<td>Post-graduate university degree</td>
<td>87</td>
<td>![Post-graduate university degree Bar Chart]</td>
<td>16%</td>
<td></td>
</tr>
<tr>
<td>Other (omitted from modelling)</td>
<td>15</td>
<td>![Other (omitted from modelling) Bar Chart]</td>
<td>3%</td>
<td></td>
</tr>
<tr>
<td><strong>Household structure (Household_str)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Couple/family with children</td>
<td>174</td>
<td>![Couple/family with children Bar Chart]</td>
<td>32%</td>
<td>9%</td>
</tr>
<tr>
<td>One-parent family with children</td>
<td>37</td>
<td>![One-parent family with children Bar Chart]</td>
<td>7%</td>
<td>3%</td>
</tr>
<tr>
<td>Couple only</td>
<td>165</td>
<td>![Couple only Bar Chart]</td>
<td>30%</td>
<td>11%</td>
</tr>
<tr>
<td>Multiple-family households</td>
<td>7</td>
<td>![Multiple-family households Bar Chart]</td>
<td>1%</td>
<td></td>
</tr>
<tr>
<td>Lone person</td>
<td>90</td>
<td>![Lone person Bar Chart]</td>
<td>16%</td>
<td></td>
</tr>
<tr>
<td>Group households</td>
<td>39</td>
<td>![Group households Bar Chart]</td>
<td>7%</td>
<td></td>
</tr>
<tr>
<td>Other one-family households</td>
<td>19</td>
<td>![Other one-family households Bar Chart]</td>
<td>3%</td>
<td></td>
</tr>
<tr>
<td>Other (omitted from modelling)</td>
<td>19</td>
<td>![Other (omitted from modelling) Bar Chart]</td>
<td>3%</td>
<td></td>
</tr>
<tr>
<td><strong>Employment status (Employ)</strong></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Full-time (paid employment)</td>
<td>241</td>
<td>![Full-time (paid employment) Bar Chart]</td>
<td>44%</td>
<td>40%</td>
</tr>
<tr>
<td>Part-time (paid employment)</td>
<td>99</td>
<td>![Part-time (paid employment) Bar Chart]</td>
<td>18%</td>
<td>16%</td>
</tr>
<tr>
<td>Self-employed</td>
<td>32</td>
<td>![Self-employed Bar Chart]</td>
<td>6%</td>
<td></td>
</tr>
<tr>
<td>Not in the work force</td>
<td>56</td>
<td>![Not in the work force Bar Chart]</td>
<td>10%</td>
<td>3%</td>
</tr>
<tr>
<td>Retired</td>
<td>54</td>
<td>![Retired Bar Chart]</td>
<td>10%</td>
<td></td>
</tr>
<tr>
<td>Student</td>
<td>40</td>
<td>![Student Bar Chart]</td>
<td>7%</td>
<td></td>
</tr>
<tr>
<td>Other (omitted from modelling)</td>
<td>28</td>
<td>![Other (omitted from modelling) Bar Chart]</td>
<td>5%</td>
<td></td>
</tr>
</tbody>
</table>

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Table 2 Main variables used in this study

<table>
<thead>
<tr>
<th>Category</th>
<th>Name</th>
<th>Description</th>
</tr>
</thead>
<tbody>
<tr>
<td>Socio-demographic</td>
<td>Income</td>
<td>Pre-tax household weekly income (in AUS): 1-99; 100-199; 200-299; 300-399; 400-499; 500-599; 600-799; 800-999; 1000-1199; 1200-1399; 1400-1599; 1600-1799; 1800-1999; 2000-2499; 2500-2999; 3000-3999; 4000-4999; 5000 or more; prefer not to answer (omitted from modelling)</td>
</tr>
<tr>
<td>Car_access</td>
<td></td>
<td>1=I don’t have access to a motor vehicle; 2=I have access to my own motor vehicle; 3=I have access to company/work vehicles; 4=I have access to a shared motor vehicle</td>
</tr>
<tr>
<td>Flexible_schedule</td>
<td></td>
<td>Flexible work/study schedule: yes; no: not applicable</td>
</tr>
<tr>
<td>Info_source</td>
<td></td>
<td>Through which sources did you primarily learn or receive travel/traffic information? TV; Radio; Newspapers (for example, Courier-Mail, Brisbane Times); Internet websites, including government websites (for example, Brisbane City Council website, Queensland Government website); Smart phone apps; Word of mouth (family, friends, co-workers, neighbours, etc.); Never checked the travel information; Other (This question was asked with respect to participants’ sourcing of information before, during, and after the flood.)</td>
</tr>
<tr>
<td>Info_importance_1</td>
<td></td>
<td>Rate the importance of travel/traffic information for your travel, regardless of source. 1=Not important at all; 2=Not important; 3=Neutral; 4=Important; 5=Very important (This rating was asked with respect to participants’ perceptions before, during, and after the flood; because of the small sample size in the category 1, this category was merged with Category 2)</td>
</tr>
<tr>
<td>Category</td>
<td>Name</td>
<td>Description</td>
</tr>
<tr>
<td>------------</td>
<td>-----------------</td>
<td>------------------------------------------------------------------------------</td>
</tr>
<tr>
<td>Primary_mode</td>
<td></td>
<td>The primary transport mode a respondent used for the typical daily trip from home: Car, Bus, Train, Bicycle, Ferry, or Other. (This question was asked with respect to participants’ primary mode before, during, and after the flood.)</td>
</tr>
<tr>
<td>Time_impact</td>
<td></td>
<td>When a respondent was planning the typical daily trip, to what extent did travel time influence the decision? 1=Not important at all; 2=Not important; 3=Neutral; 4=Important; 5=Very important. (This question was asked with respect to participants’ perception of the importance of travel time before, during, and after the flood.)</td>
</tr>
<tr>
<td>Cost_impact</td>
<td></td>
<td>When a respondent was planning the typical daily trip, to what extent did travel cost influence the decision? (This question was asked with respect to participants’ perception of the importance of cost before, during, and after the flood.)</td>
</tr>
<tr>
<td>Safety_impact</td>
<td></td>
<td>When a respondent was planning the typical daily trip, to what extent did safety influence the decision? (This question was asked with respect to participants’ perception of the importance of safety before, during, and after the flood.)</td>
</tr>
<tr>
<td>Convenience_impact</td>
<td></td>
<td>When a respondent was planning the typical daily trip, to what extent did convenience influence the decision? (This question was asked with respect to participants’ perception of the importance of convenience before, during, and after the flood.)</td>
</tr>
<tr>
<td>Mode_change_1</td>
<td></td>
<td>Relative to the primary travel mode used before the flood, did a respondent change the primary mode during the flood?</td>
</tr>
<tr>
<td>Mode_change_2</td>
<td></td>
<td>Relative to the primary travel mode before the flood, did a respondent change the primary mode after the flood?</td>
</tr>
</tbody>
</table>
1 4. Information source and perceptions of information importance

2 4.1. Information source

3 The survey data reveal that respondents often changed their primary information sources at
4 different stages of the flood, as shown in Table 2. During the event, the three most important
5 sources of travel information were TV > Internet websites > Radio. In normal circumstances,
6 however, the importance ranking of these three media is Radio > Internet websites > TV.
7 Another notable observation in this graph is that the “Never check” frequency reduced from
8 14% before the flood to 3% during the flood, and to 5% after the flood\textsuperscript{3}. This suggests that
9 respondents found travel information beneficial to their daily trips and that they tended to
10 keep using it even after the disaster. This is consistent with the comparative analysis of
11 ratings of information importance discussed later.
12
13 Percentages of the respondents who changed the primary information source at different
14 stages of the flood are summarized in Table 3. This table shows that over one third of the
15 respondents changed the primary information source at each stage. Interestingly, after the
16 flood 38% of the respondents did not return to their normal information source. To gain a

\textsuperscript{3} As commented by one reviewer, collecting the frequency of using the primary information source can provide additional information on respondents’ travel information usage pattern. Unfortunately, such question was not included in our survey.

\textsuperscript{3} Another reviewer suggested listing different types of traffic information in the questionnaire and asking participants to respond to each type of information. In the first pilot, we indeed put such questions; however, these questions like most of the questions in our survey, needed to repeat three times (before, during, after). To reduce the workload, these questions (amongst many other questions) were removed because of the scope of the study was to gauge the association between perceived importance of information and behavioural changes. Instead, such information has been indirectly obtained by asking respondents to rate the influence of time information, convenience, safety, and cost when they were making their travel decisions.
better understanding, information sources for each respondent who used a different source before, during, or after the flood were plotted in Figure 1. The horizontal lines represent no change in information source, whereas sloped lines represent a change. This figure clearly shows that among the respondents who shifted to a different information source during the flood, many of them continue using the same information source after the flood. A possible explanation is that they became used to the new information source.

Table 3 Percentages of the respondents who changed the primary information source

<table>
<thead>
<tr>
<th></th>
<th>Before flood vs. during flood</th>
<th>During flood vs. after flood</th>
<th>Before flood vs. after flood</th>
</tr>
</thead>
<tbody>
<tr>
<td>Percentage</td>
<td>43%</td>
<td>40%</td>
<td>38%</td>
</tr>
</tbody>
</table>

Finally, although Table 2 shows an almost equal use of TV and Internet during the flood, the latter is higher if the use of phone apps is included in the internet share. Meanwhile, BCC reported an unprecedented demand for its website during the flood, which resulted in its collapse for approximately 24 hours. The site was later restored, but on a limited scale (Brisbane City Council, 2011). For these reasons, the recorded shares of Internet website usage (which includes social media) and phone apps could be underestimated in this study, and it is impossible to get a definite answer on how many respondents would have used Internet during the flood. However, BCC website only collapsed about one day. And there were several other websites (e.g., Traffic and Travel Information website by Queensland Government) that provided timely updates on the flood. Thus, BCC website collapse’s impact is unlikely to be significant.

Figure 1 Change in information source
4.2. Perceptions of information importance

Survey respondents were also asked to rank the importance of travel information for their travel before, during and after the flood, using a 5-point Likert scale, where “1” is for “Not important at all” and “5” is for “Very important”. The responses are shown in Table 2.

Table 2 clearly indicates that respondents had different perceptions of the importance of travel information at different stages of the flood. To statistically test whether such change is significant, Fisher’s exact test was employed. This test is a powerful statistical significance test frequently used in the analysis of contingency tables (Agresti, 1992), especially when counts in some cells of the contingency table are small. Pearson’s chi-squared test, on the other hand, was not suitable for this data analysis because of the small numbers of respondents in some categories (for example, as was the case for the “Not important at all” category). The analysis shows that perceptions of the importance of information during the flood is significantly different from the one before the flood (that is, the p-value <0.001). Similarly, according to Fisher’s test, there is a significant difference in perceptions of the importance of information before and after the flood (that is, the p-value <0.001). A summary of the comparative analysis is presented in Table 4. It can be observed that 224 respondents (53%) changed their opinions of the importance of travel information at different stages of the flood event.

The sum of the differences of the ratings of information importance during and before the flood was calculated using the following equation

\[ \text{Sum of the rating differences} = \sum_{i=1}^{224} (R_{id} - R_{ib}) \]

where \( R_{id} \) represents respondent \( i \)'s rating of information importance during the flood, and \( R_{ib} \) represents respondent \( i \)'s rating of information importance before the flood. Other sums of the rating differences were similarly calculated.

The average change in ratings of information importance during and before the flood was calculated using the following equation:

\[ \text{average change of the rating} = \left( \frac{\sum_{i=1}^{224} (R_{id} - R_{ib})}{224} \right) \]

Other average changes in the rating were similarly calculated.

Table 4 clearly shows that compared with their perceptions of information importance before the flood, respondents generally regarded information to be more important during the flood. More specifically, on average, respondents who changed their perceptions of information importance increased the rating by more than one level; however, after the flood, respondents’ ratings of information importance decreased, as indicated by the negative signs of the sum of the rating differences, and of the average change (see the third column of Table 4).

Interestingly, the flood’s impact on the respondents’ perceptions of information importance did not totally disappear after the flood. By comparing ratings before and after the event, we
observed a hysteresis phenomenon in respondents’ perceptions of information importance. This is analogous to the widely reported hysteresis phenomenon in traffic flow research (Treiterer and Myers, 1974; Chen et al., 2012; Chen et al., 2014)**; that is, after experiencing the flood, respondents’ perceptions of information importance generally did not return to their pre-flood perceptions. Rather, after the flood, they regarded information to be more important, as indicated by the positive signs of the sum of the rating differences and of the average change (See the fourth column of Table 4).

Table 4 Summary of analysis of differences in information importance ratings

<table>
<thead>
<tr>
<th></th>
<th>Before vs. During</th>
<th>During vs. After</th>
<th>Before vs. After</th>
</tr>
</thead>
<tbody>
<tr>
<td>Fisher’s exact test p-value</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
<td>&lt;0.001</td>
</tr>
<tr>
<td>Sum of the rating differences</td>
<td>290</td>
<td>-161</td>
<td>129</td>
</tr>
<tr>
<td>Average change of 224 respondents who changed their rating</td>
<td>1.29</td>
<td>-0.72</td>
<td>0.58</td>
</tr>
</tbody>
</table>

To confirm the analysis above, these respondents’ ratings were further analysed at the individual level, as shown in Figure 2. A horizontal line and a positively sloped line in Figure 2 indicate when a respondent’s rating of information importance remained the same or increased, respectively. Of the 224 respondents who changed their rating for information importance in our survey, the majority increased their ratings during the flood – regarding information as important or very important – and only 53 respondents (24%) gave a lower rating after the flood, compared with their pre-flood rating.

Table 5 Summary of the independence tests with respect to perceived importance of information using Fisher’s exact test

<table>
<thead>
<tr>
<th>Age*</th>
<th>Gender*</th>
<th>Education</th>
<th>Income</th>
<th>Car_access*</th>
<th>Flexible_schedule</th>
</tr>
</thead>
<tbody>
<tr>
<td>0.0130</td>
<td>0.0001</td>
<td>0.6627</td>
<td>0.7761</td>
<td>0.0035</td>
<td>0.4058</td>
</tr>
<tr>
<td>Employ</td>
<td>House_str</td>
<td>Route_change_1*</td>
<td>Short_trip_cancellation*</td>
<td>Long_trip_cancellation</td>
<td>Info_source*</td>
</tr>
<tr>
<td>0.5747</td>
<td>0.1079</td>
<td>0.0015</td>
<td>0.0080</td>
<td>0.9999</td>
<td>0.0005</td>
</tr>
<tr>
<td>Primary_mode*</td>
<td>Time_impact*</td>
<td>Cost_impact*</td>
<td>Safety_impact*</td>
<td>Convenience_impact*</td>
<td>Mod_change_1*</td>
</tr>
<tr>
<td>0.0010</td>
<td>0.0005</td>
<td>0.0005</td>
<td>0.0005</td>
<td>0.0005</td>
<td>0.0025</td>
</tr>
</tbody>
</table>

* not independent at the 95% confidence level

** Traffic hysteresis was first explicitly observed in Treiterer and Myers (1974): loops exist in the relationship between density and speed from a platoon of vehicles that underwent disturbances on a freeway. In other words, after going through disturbances, the relationship between density and speed often does not follow the same path to return to the one prior to experiencing the disturbances. Generally, such hysteresis is characterized with retardation in speed recovery. Many hypotheses have been proposed to explain this phenomenon from behavioural perspective, for example, the asymmetry between acceleration and deceleration (Newell 1965; Zhang 1999), heterogeneous composition of driver population (Wong and Wong 2002; Ngoduy 2011).
To detect potential variables that may have significant linkage to changes of perceived information importance, Fisher’s exact tests were implemented and results are summarized in Table 5. This table shows that while Education, Income, Employ, House_str, and Long_trip_cancellation are not significantly associated with perceived importance of information, many other factors potentially have significant linkage to perceived importance of information such as Age, Gender, Car_access, Route_change_1, Short_trip_cancellation, Info_source, etc. While such information is important and useful (e.g., it can help to configure an initial model specification in the modelling analysis), it also implies the necessity of conducting rigorous modelling analysis using well-established statistical techniques to further scrutinize and quantify the linkage between these promising factors and perceived importance of information. Thus, in the next section, changes of perceived information importance are modelled and explained. Moreover, behavioural consequence of different perceptions on information importance is quantitatively compared, and modelled. More specifically, we investigated the potential impact of perceived importance of information on three main behavioural changes: mode changes, route changes, and trip cancellations.

5. Modelling Perceptions of the Importance of Travel Information

This section presents the modelling analysis of people’s perceptions of the importance of travel information and the impact of these perceptions on their travel behaviour at different
stages of the 2011 Brisbane flood. Binary logit and random-effects ordered logit were used to develop statistical models. Binary logit regression is a standard technique for modelling discrete outcomes (Hosmer and Lemeshow, 2004; Washington et al., 2010), and can be viewed as a special case of ordered logit. Although it can be a powerful tool, (random-effects) ordered logit is not frequently used in the transportation field (Zheng et al., 2014). Thus, a brief introduction to ordered logit and random-effects ordered logit is provided below.

5.1. Ordered logit and random-effects ordered logit

The measure of the importance of travel information – the focus of this study – is ordinal, and is measured on a 5-point Likert scale: 1 for “not important at all”, and 5 for “very important”. Unlike most categorical data, ordinal scales have a clear ordering of levels with unknown (unobservable) absolute distances between different levels. Thus, methods for analysing categorical data (for example, Multinomial Logit) are generally not suitable for analysing ordinal data; this is because different and less powerful results can be produced by ignoring the ordering information. Meanwhile, treating an ordered categorical variable as ordinal rather than nominal has many advantages, such as parsimoniousness, simpler interpretations, greater detection power, greater flexibility, and a closer similarity to ordinary regression analysis. Agresti (2010) provides a detailed discussion of the importance of utilizing the ordinality.

From the latent regression perspective, a typical formulation of the ordinal data-modelling problem is mathematically defined in Equation (1)

\[ Y = j \text{ if } \alpha_{j-1} < Y^* \leq \alpha_j \] (1)

where \( Y^* \) is a continuous latent variable that is assumed to underlie the observed ordinal data. More specifically, \( Y^* = \beta'X + \epsilon \), and \( X \) is a vector of explanatory variables; \( \beta \) is a vector of coefficients, and \( \epsilon \) is an error term; \( j \) is an ordinal response, and \( \alpha \) is a set of cutpoints of the continuous scale for \( Y^* \). In other words, \( Y \) is observed to be in category \( j \) when the latent variable falls in the \( j \)th interval.

In modelling ordinal dependent variables (for example, perceptions of the importance of travel information in this study), the logit transformation is applied to the cumulative probabilities for maintaining the category order, as shown in Equation (2):

\[ \text{logit}[P(Y \leq j)] = \log \left( \frac{P(Y \leq j)}{1 - P(Y \leq j)} \right) \] (2)

Note that the ordinary binary logit is a special case of Equation (2) when the response outcomes are collapsed into two groups, \( Y \leq j \) and \( Y > j \).

A typical model for the cumulative logits is shown in Equation (3)

\[ \text{logit}[P(Y \leq j)] = \alpha_j + \beta_1x_1 + \beta_2x_2 + \cdots + \beta_nx_n = \alpha_j + \beta'X \] (3)

where \( j = 1, \ldots, c - 1; c \) is the total number of categories; \( x_1, x_2, \ldots, x_n \) are \( n \) explanatory variables; and \( \beta_1, \beta_2, \ldots, \beta_n \) are corresponding coefficients.
Equation (3) implies that for different $j$, the explanatory variables have a common effect, as reflected by the common $\beta$, which has a significant impact on interpreting the model’s results, as illustrated by the following example.

Suppose we have two points from the explanatory variables, $X_a$ and $X_b$ (note that $X$ is a vector), then

$$logit[P(Y \leq j|X_a)] - logit[P(Y \leq j|X_b)] = \beta'(X_a - X_b)$$

Equation (4) indicates that the odds of making response $Y \leq j$ at $X_a$ are $exp(\beta'(X_a - X_b))$ times the odds at $X_b$. That is, the log odds ratio is proportional to the distance between these two points. This proportionality remains constant across different categories. Because of this property, the model in Equation (3) is often referred to as ‘a proportional odds model’. This type of model has been extensively studied and is widely used in the literature (Greene and Hensher, 2009; Agresti, 2010). Thus, it is also employed in this study.

The survey data in this study have a unique feature: They are essentially panel data because three observations (that is, before, during, and after the flood) were made for each individual. Naturally, the observations from the same individual are likely correlated. Furthermore, different individuals might have different cutpoints in their responses. The fixed effects model discussed above cannot capture such correlation and subjectivity. To overcome this issue, the model in Equation (3) is extended by introducing a random variable into the underlying latent variable model, as shown in Equation (5)

$$logit[P(Y_{it} \leq j)] = \alpha_j + (u_t + \beta_1 x_{1it} + \beta_2 x_{2it} + \cdots + \beta_n x_{nit}) = \alpha_j + (u_t + \beta' X_{it})$$

where $Y_{it}$ denotes the response for observation $t$ for individual $i$; $x_{1it}, x_{2it}, \ldots, x_{nit}$ denote the values of the $n$ explanatory variables for that observation; $u_t$ denotes the random effect for individual $i$, which is unobserved and usually assumed to vary among individuals according to a normal distribution $N(0, \sigma_u^2)$. As the variance $\sigma_u^2$ increases, the correlation between two observations from the same individual also tends to increase.

The parameters in Model (5) can be estimated by using ML (Maximum Likelihood); and, $u_t$ is estimated as the expectation of its posterior conditional distribution (given the observations) through numerical integration or Monte Carlo approximation.

5.2. **Importance of Travel Information**

The models in this study were developed mainly by using the R-package *ordinal* for analyzing ordinal data. This package is open-source, flexible, and well maintained (Christensen, 2013). The main variables that are considered in this study are summarized in Table 1 and Table 2.

(1) General

To model respondents’ perceptions of the importance of travel information before, during, and after the 2011 Brisbane flood, a series of random-effects ordered logit models were developed as a function of a variety of factors, including socio-demographic background (for example, gender and age), and the influence of travel time, cost, safety, and convenience on trip planning and primary transport mode. The dependent variable is the importance of travel information (*Info_importance_I* in Table 2), which is ordinal (that is, from 1 to 4).
These data could be treated as panel data because we obtained each respondent’s perceptions of the importance of travel information three times; namely, before, during, and after the flood. As discussed previously, to accommodate the potential correlations among the three observations of each individual, random-effects ordered logit model was appropriate. After estimating and comparing several random-effects ordered logit models, the model with the best performance was selected; this is presented in Table 6. As shown in this table, the model demonstrates an excellent fit to the data (for example, the overall performance of the model is significant at a 99% confidence level). Notable random effects exist in the data, as evidenced by the significant variance (3.404), which roughly has three implications: i) notable heterogeneity exists in our sample, such as different respondents may have different cutpoints in their responses; ii) correlation between the observations from the same individual is significant and its impact should be accounted for in modelling; and thus, iii) using random-effect models is valid.

Table 6 shows that socio-demographic features have a significant impact on respondents’ perceptions of the importance of information. When controlling for other factors and their random effects value, for a female respondent, the estimated odds of Response 4 (“[travel/traffic information] very important”, rather than “important” or “neutral”, for example) or Response 3 (“important”, rather than Response 1 or 2) increase by \((\exp(0.832) - 1) \times 100\% = 129.7\%\), relative to a male respondent. Furthermore, the older a respondent was, the more likely they were to regard the information as important. More specifically, when controlling for other factors and their random effects value, for a senior person (older than 60 years), the estimated odds of Response 4 (“very important”, rather than “important” or “neutral”, for example) or Response 3 (“important” rather than Responses 1 or 2) increase by 29.7%, relative to a respondent younger than 60.

Meanwhile, the roles of travel time and safety in respondents’ trip planning are significantly correlated to their perceptions of the importance of travel information. A higher influence of travel time or safety on trip planning corresponds to a higher perception of the importance of travel information. More specifically, when controlling for other factors and their random effects value for a respondent whose trip planning was more influenced by travel time or safety concerns, the estimated odds of Response 4 (“very important”) or Response 3 (“important”), rather than Response 1 or 2, increase respectively by 29.6% and 50.5% relative to a respondent who did not care as much about travel time or safety.

Furthermore, Table 6 indicates that different stages can have different influence on respondents’ perceived information importance. More specifically, perceived information importance during the flood is generally much stronger than those at other flood stages. After the flood, perceived information importance decreased, however, the amount of decrease was

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\(††\) A standard model development procedure has been followed in our study. Namely, after visually checking factors’ distributions, different combinations of potential explanatory factors were incorporated via logit regression, following a univariate analysis. The performance of each model was evaluated based on the theoretical soundness (e.g., signs of estimated coefficients), the p value for the overall model, and the statistical significance of each estimated parameter. The threshold p-value for the overall model performance is set to 0.05; models with overall p-values equal to or less than 0.05 were considered as candidates for the best model. Finally, a model with the best performance was selected by implementing likelihood-ratio tests and by comparing Akaike information criterion (AIC). This also applies to other models presented later in this paper.
not sufficient for perceived information importance to return to the level reported at the
before flood stage. This has also confirmed the hysteresis phenomenon discussed in Section
4.2.

Finally, to shed more light on this issue, separate models have also been developed for
different flood stages, and summarized in tables A - C in Appendix. Again, consistent results
have been obtained, which underscores the trustworthiness of the results above.

Table 6 Outputs of the model for perceived importance of information before, during, and
after the flood

| Attributes      | Parameters | Standard error | z    | Prob |z|>z* |
|-----------------|------------|----------------|------|------|-----|
| Female          | 0.832      | 0.210          | 3.962| <0.001 |
| Age             | 0.260      | 0.073          | 3.542| <0.001 |
| Time_impact     | 0.259      | 0.074          | 3.503| <0.001 |
| Safety_impact   | 0.409      | 0.075          | 5.427| <0.001 |
| During_flood    | 2.000      | 0.166          | 12.067| <0.001 |
| After_flood     | 0.682      | 0.129          | 5.295| <0.001 |

Threshold coefficients: 1|2→0.373, 2|3→2.718; 3|4→6.007

(2) Before the flood vs. during the flood

To better understand respondents’ perceptions of the importance of information and their
potential effect on their travel behavior during the flood, binary logistic models of their travel
mode changes, route changes, and trip cancellation, as functions of a variety of explanatory
variables, were developed. The specific purpose of the modeling was to pinpoint whether
different perceptions of the importance of information had different impacts on respondents’
travel mode changes, route changes, and trip cancelling during the flood. Despite the obvious
importance of this knowledge to the effective and efficient management of transport networks
in abnormal conditions (such as the flood in this study), there is little investigation of this
relationship reported in the literature.

While the analysis shows no significant association between respondents’ mode changes and
their perceptions of the importance of information, it clearly shows a significant correlation
between the latter and respondents’ route changes, as summarized in Table 7. Table 7 shows
that when controlling for other factors, for a respondent who thought that information was
important, the estimated odds of changing routes increases by 192.7%, relative to a
respondent who thought that information was not important.

Meanwhile, the analysis also reveals a significant correlation between respondents’ trip
cancellations (short-trip cancellation in Table 2) and their perceptions of the importance of
information, as shown in Table 8. More specifically, when controlling for other factors, for a
respondent who thought that information was important, the estimated odds of cancelling trips increases by 627.9%, relative to a respondent who thought that information was not important.

Table 7 Outputs of the model for changing routes during the flood

| Attributes          | Parameters | Standard error | z     | Prob |z|>z* |
|---------------------|------------|----------------|-------|------|-----|
| Constant            | -0.968     | 0.314          | -3.085| 0.002|
| Age                 | -0.142     | 0.069          | -2.066| 0.04 |
| Info_importance_2   | 1.074      | 0.228          | 4.710 | <0.001|

Note: i) Info_importance_2 is derived from Info_importance_1; travel/traffic information was important when Info_importance_1 >3, travel/traffic information was not important otherwise; and ii) Age and Info_importance_2 are not significantly correlated according to Fisher’s exact test (p-value = 0.86).

Table 8 Outputs of the model for cancelling trips during the flood

| Attributes          | Parameters | Standard error | z     | Prob |z|>z* |
|---------------------|------------|----------------|-------|------|-----|
| Constant            | -1.742     | 0.221          | -7.872| <0.001|
| Info_importance_2   | 1.985      | 0.244          | 8.143 | <0.001|

Note: Info_importance_2 is derived from Info_importance_1; travel/traffic information was important when Info_importance_1 >3, travel/traffic information was not important otherwise.

(3) Before the flood vs. after the flood

Potential links between respondents’ perceptions of the importance of information and the influence on their travel behavior after the flood were similarly analysed. Binary logistic models for respondents’ mode and route changes as functions of a variety of explanatory variables were developed for the specific purpose of pinpointing whether respondents’ different perceptions of the importance of travel information have different impacts on mode and route changes after the flood, relative to before the flood.

Again, no significant association between respondents’ mode changes and their perceptions of the importance of information is indicated. However, as shown in Table 9, the analysis reveals a negative relationship between respondents’ route changes and their perceptions of the importance of travel information. This is different to the finding for the actual duration of the flood event. This is not surprising because during normal conditions (that is, after the flood), the more information a respondent gathers, the more confidence they generally have in the ‘normality’ of their route, and the less likely they are to change it. Behavioral-inertia might be another reason why some respondents did not change back to their regular route used before the flood. To shed more light on this issue, the respondents were divided into two groups to scrutinize the role of “behavioural inertia” in this phenomenon: one for those who chose “I’m used to this new route” (i.e., the behavioural-inertial group), and one for those
who did not choose it. Only 7 (4%) respondents belong to the behavioural-inertial group. This variable was added into the model as a dummy variable, and turned out insignificant. We also repeated the modelling procedure by excluding these 7 respondents. Not surprisingly, modelling results are almost identical as in Table 9. Thus, behavioral-inertia does not have significant impact in our study.

Meanwhile, note that the importance of information is not a significant factor in route changing, as indicated by the large p-value (that is, \( p=0.336 \)), which implies that information becomes less important during a normal period.

Table 9 Outputs of the model for changing routes after the flood

<table>
<thead>
<tr>
<th>Attributes</th>
<th>Parameters</th>
<th>Standard error</th>
<th>z</th>
<th>Prob</th>
<th>z</th>
<th>&gt;z*</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-0.122</td>
<td>0.311</td>
<td>-0.393</td>
<td>0.694</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>0.315</td>
<td>0.073</td>
<td>4.309</td>
<td>&lt;0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Info_importance_2</td>
<td>-0.218</td>
<td>0.227</td>
<td>-0.963</td>
<td>0.336</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

Note: i) Info_importance_2 is derived from Info_importance_1; travel/traffic information was important when Info_importance_1 >3, travel/traffic information was not important otherwise; and ii) Age and Info_importance_2 are not significantly correlated according to Fisher’s exact test (p-value = 0.24).

Another noteworthy observation is age’s significant impact on route changing both during and after the flood. From the modelling analysis for during the flood (see Table 7), the parameter of age is negative, which means that when other factors are equal, it is generally harder for older respondents to change routes in the first place; in the contrast, from the modelling analysis for after the flood, the parameter of age is positive (see Table 9), which means that when other factors are equal, it is generally easier for older respondents to change back to their old routes once the situation is normal. In summary, generally older respondents had a stronger attachment to the routes they normally use.

6. Conclusions

Using the 2011 Brisbane flood as a case study, this paper provides an empirical analysis of respondent survey data to determine the flood’s impact on their travel behaviour. The main contribution of this study is that perceptions of the importance of information and their potential impact on travel behaviours have been modelled and explained. This is important, as the issue is seldom explored in the literature. The study’s main findings are summarized below.

During the flood, TV was the most important sources of travel information, which is consistent with studies based on hurricane evacuation (e.g., Prater et al., 2000).

A hysteresis phenomenon in respondents’ perceptions of the importance of information is consistently observed in our analysis. Namely, because of the flood, perceptions of the importance of information were increased, and although its perceived importance decreased...
after the flood, it did not return to pre-flood perceptions. Despite the apparent analogy between the hysteresis in perceived information importance and in the speed-density relationship as previously discussed, underlying reasons for triggering them should be very different. While the traffic hysteresis is likely caused by behavioural reasons, the hysteresis in perceived information importance is likely caused by psychological reasons: because of experiencing the flood, the importance of information has been reinforced, which makes many respondents to perceive information’s importance more favourably even after the flood. A question worthy of further investigation is: how long does such influence last?

As reported in the literature (e.g., Sadri et al., 2013), socio-demographic features have been found to have a significant impact on respondents’ perceptions of the importance of travel information. For the survey sample in this study, females tend to think that information is more important than their male counterparts do. In addition, older respondents displayed a stronger attachment to the routes they normally use, that is, when other factors are equal, older respondents are more reluctant to change routes in the first place, and more willing to change back to their old routes once the situation is normal. In the literature, gender and age are two often-reported determinants of risk attitudes heterogeneity, which partially explain gender difference and age differences in social behavior (e.g., Barsky et al., 1997; Dohmen 2005; Dohmen et al., 2011). More specifically, it is often reported that women are less willing to take risks than men (e.g., Barsky et al., 1997; Dohmen et al., 2011). Thus, to reduce risks, as revealed in our analysis, females tend to treat information in the 2011 Brisbane flood more seriously than males. In addition, willingness to take risks generally decrease with age (e.g., Dohmen et al., 2011), which implies a stronger behavioral inertia for older people. This explains why older respondents displayed a stronger attachment to the routes they normally use in the 2011 Brisbane flood.

Meanwhile, the roles of travel time and safety in respondents’ trip planning are significantly correlated to their perceptions of the importance of information. A higher influence of travel time and safety on respondents’ trip planning corresponds to their perceptions of the greater importance of information. In contrast, no significant correlation between travel const and perceptions of the importance of information was found, which is not surprising because for a respondent whose focus is to minimize travel cost, factors other than information (for example, transport mode, or travel experiences) are likely to play a more important role in their trip planning.

Meanwhile, the analysis identifies the relative importance levels of information during and after the flood. During the flood, respondents generally thought that the information was important, and adjusted their travel plans accordingly (by either changing routes or cancelling trips). Furthermore, the substantial behavioural consequences of various perceptions of the importance of information are highlighted by the magnitude of difference in the estimated odds. When controlling for other factors, the estimated odds of changing routes and cancelling trips for a respondent who thinks that the information is important, are respectively about three and seven times the estimated odds for a respondent who does not consider it important. On the other hand, after the flood period, the influence of information on respondents’ travel behavior diminishes.
Finally, the analysis provides no evidence of the influence of information on changes in respondents’ travel mode. This confirms the phenomenon that is frequently reported in the literature (Wesemann et al., 1996); that is, inducing changes in travel mode is generally very challenging. According to Goodwin (1977) the “habit” effect makes it more difficult to reverse a trend than to accentuate it; this could be one reason why travellers show a great resistance to changing modes, even during and after an extreme event. Another reason could be that mode change can involve a major shift in lifestyle, and is constrained by other factors such as car ownership, accessibility to and level of service of public transit.

Findings of this study enhance the understanding of the impact of natural disasters on travel behavior, an area of high importance, yet currently given insufficient consideration and coverage in the literature, primarily due to data limitations. More specifically, insights into perceptions of the importance of travel/traffic information and the consequential changes in travel behavior can be used to design more effective information systems for travelers, and more efficient traffic management strategies – two critical components of disaster response systems, e.g., better selecting targeted age group (and thus selecting most attractive media); integrating alternative routes information and trip cancellation suggestion into information provided during a flood; not wasting resources in attempting to persuade travellers to change their transport modes, and etc.

Finally, conclusions in this study are based on the 2011 Brisbane flood; whether they can be generalized to other types of disasters needs further study; meanwhile, as suffered by most studies relying on statistical techniques, causation between perceived importance of travel/traffic information and behavioural changes needs to be verified.

Acknowledgements: The authors were grateful for insightful and constructive comments from anonymous reviewers and from Editor Dr. Pamela Murray-Tuite, which have significantly improved this paper’s quality. This research was partially funded by Queensland University of Technology.

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Appendix Separate Models for Different Flood Stages

Table A Outputs of the model for perceived importance of information before the flood

| Attributes      | Parameters | Standard error | z     | Prob | |z|>z* |
|-----------------|------------|----------------|-------|------|-----|
| Female          | 0.427      | 0.168          | 2.535 | 0.01 |     |
| Age             | 0.108      | 0.060          | 1.801 | 0.07 |     |
| Time_impact     | 0.255      | 0.076          | 3.363 | <0.001 |     |
| Safety_impact   | 0.245      | 0.08           | 3.179 | 0.001 |     |

Threshold coefficients: 1|2 → 0.380, 2|3 → 1.886; 3|4 → 3.673

Table B Outputs of the model for perceived importance of information during the flood

| Attributes      | Parameters | Standard error | z     | Prob | |z|>z* |
|-----------------|------------|----------------|-------|------|-----|
| Female          | 0.684      | 0.216          | 3.169 | 0.002 |     |
| Age             | 0.344      | 0.078          | 4.405 | <0.001 |     |
| Time_impact     | 0.249      | 0.105          | 2.369 | 0.02  |     |
| Safety_impact   | 0.597      | 0.111          | 5.361 | <0.001 |     |

Threshold coefficients: 1|2 → 0.777, 2|3 → 2.228; 3|4 → 5.085

Table C Outputs of the model for perceived importance of information after the flood

| Attributes      | Parameters | Standard error | z     | Prob | |z|>z* |
|-----------------|------------|----------------|-------|------|-----|
| Female          | 0.435      | 0.177          | 2.456 | 0.01 |     |
| Age             | 0.191      | 0.063          | 3.036 | 0.002 |     |
| Time_impact     | 0.337      | 0.091          | 3.720 | <0.001 |     |
| Safety_impact   | 0.270      | 0.089          | 3.012 | 0.003 |     |

Threshold coefficients: 1|2 → 0.059, 2|3 → 1.982; 3|4 → 4.259