Improving the experience for rail passengers and operators by providing improved crowding information

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Abstract. Crowded trains diminish the experience of rail passengers through discomfort, stress, and a reduction in productivity. Variations in crowding affects rolling stock utilisation and dwell times at busy stations, impacting rail operators. This research explores the benefits of providing improved train crowding information to passengers (to encourage travel on less-crowded trains) and staff. Both information presentation and data collection technologies were considered, revealing further avenues of investigation requiring systematic application of human factors methodologies.

Keywords. Crowding; information provision; data; passenger behaviour.

1. Introduction

Overcrowding of rail services in major cities has become a worldwide problem, for which finding solutions is a big challenge for authorities (Henn, Karpouzis, & Sloan, 2010). Crowded trains have negative consequences for both passengers and operators. Studies suggest that when between 50% and 70% of the seats on the train are occupied then passengers experience a disutility such as reduced physical comfort, lower productivity, or increased stress levels (Cox, Houdmont, & Griffiths, 2006; Pel, Bel, & Pieters, 2014). In addition to the reputational damage risked by operators when passengers have a negative experience, it has also been found that delays on commuter trains invariably increase with passenger density (Cox et al., 2006). This makes it harder for operators to provide a reliable service (and has additional negative consequences for passengers).

Whereas it is clear from the literature that rail passengers do exhibit a tendency to change their behaviour in response to crowding – for example, by departing earlier or later to avoid crowding, waiting for a less crowded service, departing from a different station, or choosing a less crowded carriage (Pel et al., 2014) – it is also evident that such behavioural change is not as common as the disutility associated with crowding might suggest (Wardman & Whelan, 2011). There may be a number of good reasons for this, but a key factor is likely to be insufficient information about crowding levels (Pritchard, 2017); it is hard for passengers to make a reasoned choice about whether it is worth making alternative plans (such as waiting for a later train) when crowding levels are rarely communicated (Preston, Pritchard, & Waterson, 2017). Stated preference studies conducted on train services in the UK between London, Gatwick Airport and Brighton (Pritchard, 2017) reinforce the idea that better information about crowding levels does have the potential to encourage further behavioural change, benefitting both passengers and operators. For passengers, the ability to make an informed decision can increase the sense of being in control (and may therefore reduce some of the stress associated with travelling on a crowded train), and can assist those who have sufficient flexibility in finding a train on which they can be more comfortable and more productive. As well as potentially benefitting those who
are willing and able to change their travel behaviour, it may additionally allow those who stick with their travel habits to benefit from reduced crowding levels. Rail operators also stand to benefit if information provision is successful in encouraging behavioural change – a uniform spread of passengers means better capacity utilization and a reduced risk of excessive boarding and alighting times. Operators can also benefit more directly from having access to crowding information themselves, as it can aid them in their service planning (both long-term and short-term, in the event of disruption).

The first part of this paper summarises the results from the earlier stated preference work, showing the willingness of different passenger groups to respond to crowding information. The second part of this paper summarises some of the challenges involved in making the provision of crowding information a reality, giving some insight into ongoing work with a Train Operating Company (TOC). The third part of this paper summarises the variables identified, assumptions made and questions raised, and discusses how Human Factors methodology could be used to inform effective information provision to influence passenger behaviour and support operations.

2. Stated Preference Surveys

2.1 Methodology

On-train surveys were conducted on-board Gatwick Express services between London Victoria, Gatwick Airport and Brighton, with the full co-operation of the train operator (Govia Thameslink Railway). The surveys were undertaken using tablet PCs, and used stated preference (SP) methodology to ascertain how passengers might change their behaviour when presented with crowding information. Participants were asked some questions about their journey and were given three SP exercises. The first was concerned with choosing a train when planning a journey in advance, whilst the second and third were concerned with information at the station, considering choice of train and choice of carriage respectively. This paper focuses on the information presented at the station.

When considering the choice of train, the research sought to understand the willingness of passengers to wait for a later train if the first one was crowded. Survey participants were given a set of six pairs of upcoming departures from their origin station. The first train (given as ‘Due’) was always shown to be crowded, with no seats available. A second train, assumed to follow the same route and journey timings, was shown departing a number of minutes later and with a reduced level of crowding. Participants were asked to choose one of the departures, with the wording in the full study making it clear that the choice was between boarding the current train or waiting at the station. Each of the six cases – shown to participants in a random order – contained a variation on either the time gap until the second train or on its level of crowding. Some participants were randomly chosen to be given crowding information in a graphical format, whilst the others were given numbers of seats in a text-based format; examples of the displays used in the full study are shown in Figure 1. In the graphical case, red was used to represent no available seats, orange represented an occupancy level of 60%, and green represented an occupancy level of 10% of the number of seats. When text-based information was given instead, the numbers of seats given followed this same pattern, and was based upon the rolling stock used on the route at the time. The intermediate level of crowding was set at an occupancy of 60% of the number of seats, because it corresponds to the threshold at which crowding impacts typically begin to be felt (Wardman & Whelan, 2011).
When considering the choice of carriage, the survey was based on a sample three-carriage train formation, with carriages labelled A, B and C. An illustration of the formation was shown to participants, in which the entrance to the platform at the origin station was given as being closest to Carriage B (in the middle), and the exit from the platform at the destination station was given as being closest to Carriage A (the leading carriage). The SP exercise then comprised nine example display boards in a random order; Carriage B was always given as having no seats available, and the crowding levels of carriages A and C were varied. Consistent with the exercises concerning the whole train, red represented a crowded carriage (no seats available), orange represented a busy carriage (60% of seats occupied) and green represented an empty carriage (10% of seats occupied). A sample display board is shown in Figure 2. All participants were shown graphical information; there was no text-based alternative.

For each SP exercise, the statistics package Stata was used to fit alternative specific constant logit models (McFadden’s Choice Model) to the data collected (McFadden, 1973; StataCorpLP, 2016) to the data collected (Preston et al., 2017; Pritchard & Preston, 2017). The coefficients of the models were used to infer the importance of the different factors for participants when choosing a train or carriage, such as the availability of seats, the time between trains and the proximity of the carriage to the ticket barrier. For the choice of train, a ‘willingness to wait’ metric was devised – effectively an estimate, in minutes, of how long, in minutes, passengers would be willing to wait for a less crowded train. In order to understand the potential impact of information on different people, the data were divided into different groups, each of which was analysed separately. For the first of the two SP exercises (choice of train), the passenger groupings were as follows:
1) Morning Commuters. Commuters travelling in the morning peak period between 6am and 9am. Airport users were excluded.
2) Evening Commuters. Commuters travelling in the evening peak period between 4pm and 7pm. Airport users were excluded.
3) Other Business Passengers. Non-commuting business passengers, irrespective of time of day. Airport users were excluded.
4) Non-airport leisure passengers. Leisure passengers who were not airport users.
5) Leisure Passengers with a flight to catch. Leisure passengers who had specifically stated that they were flying out of Gatwick Airport.

The term “airport users” refers to those who were either flying in or out of Gatwick Airport, and does not include those who used the station at Gatwick for other reasons. Business passengers with a flight to catch were not treated separately, because not enough of them were surveyed to give meaningful data. Similar groupings were used for the second SP exercise (choice of carriage), although morning and evening commuters were treated together because there was no time dependency.

2.2 Results
In general terms, the model coefficients which were generated matched expectations; a reduction in crowding (or an increase in the number of available seats) was a positive factor, whilst the time associated with having to wait for a later train was a negative factor (Preston et al., 2017). The value-of-time multipliers associated with a crowded train were estimated from the model coefficients, and were found to be consistent with existing literature. When choosing a carriage, proximity to the ticket barrier at the destination station was important for commuters, but insignificant for everyone else; presumably because non-commuters travelling outside peak times rarely encounter queues at the ticket barrier in the same way (Pritchard, 2017). To show the variation between different passenger groups when considering the choice of train, the calculated values for the willingness to wait metric are given in Table 1. In some cases, the relevant coefficients were not found to be significant, which is why values are not given for each case.

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<tbody>
<tr>
<td>Morning commuters</td>
<td>14</td>
<td>-</td>
<td>20</td>
<td>-</td>
</tr>
<tr>
<td>Evening commuters</td>
<td>17</td>
<td>-</td>
<td>17</td>
<td>-</td>
</tr>
<tr>
<td>Other business passengers</td>
<td>19</td>
<td>25</td>
<td>22</td>
<td>28</td>
</tr>
<tr>
<td>Non-airport leisure passengers</td>
<td>12</td>
<td>26</td>
<td>19</td>
<td>33</td>
</tr>
<tr>
<td>Leisure passengers with a flight to catch</td>
<td>-</td>
<td>-</td>
<td>9</td>
<td>28</td>
</tr>
</tbody>
</table>

It is not surprising that those with a flight to catch are the least willing to wait for a later train, although the gap between those who were shown graphical information and those who were shown text-based information needs further research. Leisure passengers in general would
seemingly much prefer text-based information than graphical information, but it is likely that this result highlights some unintended consequences of information provision. A high proportion of those using the airport were not UK residents, did not have English as their first language, and may not have been familiar with the system. For those given graphical information, the colors may have implied other issues (e.g. orange is often associated with a warning) whilst those given text-based information may have (incorrectly) inferred that zero availability of seats meant that it was not possible to board the train at all.

On the other hand, text-based information given to commuters did not yield significant results. This might reflect the fact that they expect the train to be crowded, and any perceived benefits of reduced crowding (e.g. less discomfort) are not tied to a guarantee of a seat (Pritchard, 2017). Although graphical crowding information would appear to induce some behavioural change amongst commuters, it could be argued that the impact in reality is likely to be minimal on the whole – despite the Gatwick Express having a 15 minute service frequency at peak times, stated preference surveys can suffer from a non-commitment bias and may overstate the likely reality (Preston et al., 2017). Context is important, however, because the research found a marked difference between morning commuters boarding at Brighton (a well-equipped terminal station) and nearby intermediate stations, which are typically smaller and lacking in facilities – considering Brighton alone, the willingness to wait amongst morning commuters increases to 23 minutes, compared with just eight minutes for the smaller stations.

Non-commuting business passengers showed the greatest willingness to wait. They responded much better to text-based information about seating availability, and were also more willing to wait if the later train had many seats available. This suggests that getting a seat is more important than simply having a reduced level of crowding, and may be tied to a need to use the travel time productively, and the fact that this sort of business trip may be longer than a regular commute.

3. The practicalities of providing crowding information

Having ascertained that better provision of crowding information has the potential to be influential for some groups of passengers, work is continuing with Govia Thameslink Railway to implement a trial system so that the benefits can be further assessed. Although some information is already available on some routes in the UK, there are generally limitations. For example, the information provided by London Midland (2016) is static, based on historical data, and may not reflect current reality (especially in the event of disruption). It is also only provided on a per-train basis, which does not help passengers at the station decide which carriage to board – although other operators have now begun to include reservation information on the Customer Information Systems at stations (Infotec, 2016). More globally, there is evidence of investment in real-time crowding information provision on a per-carriage basis (Japan Today, 2014), but potential barriers to wider implementation of the technology include cost, reliability, and the availability of the supporting infrastructure (Pritchard, 2017).

In order to provide real-time crowding information, it is important to know both how many people are on a given train at the moment, and to predict how many people will be on the train at a specified future point. Long-range predictions are desirable for passengers planning a journey
in advance, or for operators who are reviewing their timetable and rolling-stock allocations, but predictive capabilities are also necessary for much more immediate decision making. Reporting a train as being full and standing as it approaches a station may unhelpfully influence passenger behaviour if most of the occupants are due to alight when it arrives at the station.

The ongoing work seeks to investigate how these aims might be achieved, utilising existing data sources where possible; making use of existing systems and infrastructure can help overcome the barrier of cost. The available data sources can be categorized as follows (Pritchard, 2017):

1) Sources tied to a physical train (e.g. data from onboard equipment).
2) Sources tied to a particular station, which may help inform the number of people on a train (e.g. data from ticket barriers which counts the number of people going on to the platform).
3) External data sources.

On-train data includes loadweigh sensors (which measure the weight carried within each carriage) and numbers of devices using on-train WiFi. Station data include numbers of people passing through ticket gates and numbers of users of at-station WiFi. It also includes additional bespoke sources, such as data from a device which is able to count people passing in front of it by counting pairs of shoes. External data sources include data from mobile network operators. None of the data sources are perfect; for example, estimating the number of people from the loadweigh sensors in a carriage requires assumptions to be made about the average weight of a person. There are even more challenges on a service such as the Gatwick Express, when at certain times of the day many of the passengers are travelling to the airport and carrying significant amounts of luggage. Ticket gates may span a number of platforms (and hence cover a number of arriving/departing trains), and may not be in constant operation, whilst the number of devices connected to a WiFi network is not consistent with the number of people; it is not unusual for some passengers to have multiple devices. Further detail about some of the advantages and disadvantages of different sources are given in earlier work (Pritchard, 2017).

It is likely that a combination of data sources will be required to accurately estimate the number of people on a train – although the required accuracy will be dependent on the format of the information required. For example, loadweigh sensors may on their own be sufficient to provide graphical crowding information using a ‘traffic-light’ system or similar with only a few levels. In this instance, the aim is simply to provide an indication of crowding levels, so not being able to distinguish between, for example, four people or three people with luggage is likely to be immaterial. In fact, in some cases, it could be argued, that luggage and other items also contribute to the negative effects of crowding (e.g. lack of personal space), and load weight alone may be a good metric. It was clear from the stated preference survey work, however, that providing numbers of available seats is important, particularly for some passenger groups. This is more difficult to ascertain and predict reliably, but it is important – in all cases – that the information provided can be relied upon. Passengers who decide to trade the inconvenience of waiting for a later train in order to get a seat will likely experience an increase in frustration if, they alter their travel plans and aren’t rewarded with somewhere to sit. It could be argued that unreliable information is more damaging than no information at all, and it would not be unreasonable to expect someone who has felt let down by the information which is provided to be less willing to change their behaviour in response to it in future.

There are two separate concerns when it comes to addressing some of the reliability concerns.
The first is to ensure that the underlying data are accurate – so any system which estimates the number of seats on a train must be technically robust. The second is to ensure that expectations are well managed; if the system correctly reports that there are 20 seats available on a subsequent train, there will still be crowding problems if 25 people each interpret this as an available seat for them and decide to wait.

4. Identifying Relevant Human Factors (HF) methodologies

The work so far has identified a number of variables for consideration, made key assumptions, and raised many questions. This section provides a summary and identifies relevant HF methodologies that could be applied for further investigation, to better inform the provision of information to passengers and to support rail operations.

The variables arising from this initial research are summarised in Table 2. These relate to the variables the research outlined in this paper aims to influence (such as crowding levels, passenger comfort, boarding and alighting durations), as well as variables that could be categorized as relating to: a) Information displays, b) the infrastructure and rail network, and c) the passenger and their journey.

Table 2 - Variables arising from initial research, categorized by type

<table>
<thead>
<tr>
<th>Variables to influence:</th>
<th>Variables related to information displays:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Crowding levels</td>
<td>- Type of information display</td>
</tr>
<tr>
<td>- Boarding and alighting durations</td>
<td>- Content of information display</td>
</tr>
<tr>
<td>- Change in behaviour</td>
<td>- Reliability of information display</td>
</tr>
<tr>
<td>- Use of information provided</td>
<td>- Location of information display</td>
</tr>
<tr>
<td>- Passenger comfort</td>
<td>- Perceived reliability of information provision</td>
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<tr>
<td>- Passenger productivity</td>
<td></td>
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<tr>
<td>- Passenger stress</td>
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<table>
<thead>
<tr>
<th>Variables relating to the infrastructure and rail network:</th>
<th>Variables relating to the passenger and their journey:</th>
</tr>
</thead>
<tbody>
<tr>
<td>- Number of ticket barriers (and hours of operation)</td>
<td>- Passenger type (e.g. based on purpose of journey)</td>
</tr>
<tr>
<td>- Frequency of service</td>
<td>- Passenger attributes (e.g. ability to interpret information)</td>
</tr>
<tr>
<td>- Available facilities at stations</td>
<td>- Flexibility of passenger</td>
</tr>
<tr>
<td>- Available data sources</td>
<td>- Anticipated use of journey time (e.g. computer based work, reading, conversation)</td>
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Supply and demand ratio for available seats

- Intended boarding and alighting stations
- Luggage to passenger ratio
- Length of commute compared to typical journeys

Some of these variables lend themselves to manipulation in order to influence passenger
behaviour; this is particularly true for those relating to information displays, but may also be true of others, such as the service frequency. Some variables, although within the control of rail operators, may have significant barriers to change, especially when taking in to account cost. Such variables may include the facilities at boarding stations, the number and position of ticket barriers, and the available data sources. Finally, there are variables broadly outside the control of rail operators, particularly those relating to the passenger and journey, such as the type of passenger, their anticipated use of travel time, their origin and destination stations, and how much luggage they will take. When considering the application of HF methods, it is clear that the rail domain can be considered to be a ‘complex system’, due to the large number of interacting variables with varying capacity for control.

A key assumption made in this research is that better information about crowding levels could encourage behaviour change amongst some passengers. It is also assumed that this change in behaviour would occur through an ability to make informed decisions. Methods investigating decision-making, such as the Critical Decision Method (CDM) by Klein and Armstrong (2004), would enable this assumption to be tested. CDM is a semi-structured interview technique that is used to elicit specific information regarding the decision-making strategies used by agents in complex, dynamic systems (Neville A. Stanton, Salmon, & Rafferty, 2013).

It is also clear that there are many constraints within the rail industry on the real-time provision of crowding information (related to e.g. existing infrastructure and systems, operational practices, on-board equipment, and station design). If access to appropriate subject matter experts (SMEs) is granted, a more comprehensive HF analysis could be undertaken, through the use of Cognitive Work Analysis (CWA) (Vicente, 1999). CWA is a formative ‘constraints based’ HF method that was developed to model the behaviour that can occur in complex sociotechnical systems. This method contains a number of phases well suited to gaining insights relating to passenger crowding behaviour, including Work Domain Analysis, Activity Analysis and Strategies Analysis and Competencies Analysis (Neville A. Stanton et al., 2013). CWA also focuses on decision making strategies through the use of ‘Decision Ladders’ (DLs), which could be adopted to further explore the key assumptions made.

There is a case for promoting behavioural change in order to reduce crowding and even out passenger loadings. To determine if a behaviour change results from an intervention (such as improved information provision), methods of capturing and predicting behaviour (e.g. passengers deciding to change their journey plan), rather than simply observing potential outcomes of behaviour change (i.e. lower levels of crowding) are necessary. Generic HF methods such as observation, interviews and questionnaires would serve data capture needs (Neville A. Stanton et al., 2013) and should be applied both before and after interventions are made. Data from these sources would then benefit from being fed into depiction methods such as Hierarchical Task Analysis (HTAs) (Annett, 2004; Neville A. Stanton, 2006) to enable deconstruction of passenger behaviour, or Operational Event Sequence Diagrams (OESDs) (Ainsworth & Kirwan, 1992) to highlight how passengers interact with other agents (staff, technology, other passengers) in their journey and decision making behaviour. Differences in the outputs though application of these methods could then be compared. The outputs from HTAs can also act as the input into more comprehensive methods such as CWA for some phases.
of analysis.
Finally, the research to date has raised a number of pertinent questions, including:
- Why don’t people choose less crowded trains more often, given the negative experience of overcrowding?
- How do information needs differ between different passenger types?
- What information is needed in order to make an ‘informed decision’?
- What amount of flexibility is sufficient for information provision to lead to behaviour change?
- What is the value of a seat compared to waiting time for different users?
In addition to a comprehensive literature review, answering these questions requires more in-depth understanding from passengers themselves, to better articulate the dependencies, and their needs when making decisions about their journey. Generic HF methods such as interviews and focus groups would suit this purpose well (Neville A. Stanton et al., 2013).

5. Conclusion

It is clear that provision of information to reduce overcrowding in trains is not a trivial endeavour, but initial results suggest value in its pursuit. There appears to be potential for better information about crowding to be influential amongst, and beneficial for, certain groups of passengers. However, the implementation of reliable and effective real-time crowding information presents a number of challenges.

From a human factors perspective, the rail domain must be recognized as a complex system and a number of methods have been identified to progress systematic exploration. These fall into generic data collection methods (observations, interviews and focus groups), data representation methods (HTAs, OESDs) and methods tailored to understanding complex systems with an emphasis on decision making (CDM, CWA). The insights gained from application of these methods could enable specification of the requirements for information-based interventions aimed at reducing crowding.

6. Acknowledgements

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7. References


