Australasian Transport Research Forum 2015 Proceedings
30 September - 2 October 2015, Sydney, Australia
Publication website: http://www.atrf.info/papers/index.aspx

Influencing Passenger Egress to Reduce Congestion at Rail Stations

Nathan Kirchner[1], Sonja Caraian[1], Peter Colborne-Veel[1], Michelle Zeibots[2]

[1]Centre for Autonomous Systems, University of Technology, Sydney, Australia

[2]Institute of Sustainable Futures, University of Technology, Sydney, Australia

Email for correspondence: nathan.kirchner@uts.edu.au

Abstract

As rail station patronage levels increase, so too does the load on the entire railway system. The higher passenger densities exacerbate local egress issues and thus adversely affect dwell time and subsequently punctuality, along with the passenger experience. Devices such as barriers are regularly used to influence passenger egress. However, their use is typically limited to special events; where perhaps a single influence-objective is intended on a relatively uniform passenger demographic. This limitation precludes such devices usefulness for daily operations; where potentially multiple influence-objectives, which potentially change regularly, exists. Furthermore, it is reasonable to expect a considerably less uniform passenger demographic which perhaps includes passengers that are less receptive to particular influence strategies.

This paper presents an exploration of components of a robotic system that is responsive to real time person behaviours and operator’s needs. Specifically, details of our methods for identification of the passenger demographic groups and passenger egress influencing are presented along with results from two studies. The first study was conducted at Townhall Station Sydney and explored our robotic system’s ability to reliably identify the passenger demographic of individual passengers in real time. The ability of our robotic system to influence real time egress of real in-transit passengers in situ, and the ability to responsively moderate influence-objective based on observed characteristics was explored in the second study which was co-located at Perth Station Perth and the University of Technology Sydney. Finally, this paper discusses how this predictable influence of passenger egress can potentially be leveraged to benefit operations.

1. Introduction

Passenger egress behaviour, and the subsequent over crowding, causes service reliability issues, limits operational capacity, and has tractable costs [Gray, 2013, Veitch et al., 2013, Wang and Legaspi, 2012]. In such, operators expend considerable efforts treating this behaviour. Typically though, due to the complexity and situational dependent nature of these behaviours, these treatments are static. For instance, devices such as barriers are regularly used to influence passenger egress. However, their use is typically more suited to special events where perhaps a single influence-objective is intended on a relatively uniform passenger demographic. This limitation precludes such devices usefulness for daily operations; where regularly changing multiple influence-objectives potentially exists. Furthermore, it is reasonable to expect a considerably less uniform passenger demographic which perhaps includes passengers that are less receptive to particular influence strategies. Many situations exist in which influencing behaviour in congested train stations as part of daily operations would be useful. The ability to influence the movement of people could reduce collisions on blind corners, or increase the efficiency of passenger flow through bottlenecks such as passageways and stairwells by influencing people to a particular side.

This raises the question: how can people’s behaviour be influenced? Our ongoing research has focused on exploring this question through investigating influence during Human-Robot Interaction (HRI). For instance, we demonstrated a robot measurably influencing human decision-making in [Caraian and Kirchner, 2013a, Caraian and Kirchner, 2013b]. Similarly, we demonstrated robot instantiated interaction with naïve passersby, and influence of egress and physical interaction upon a particular individual within a crowd in [Kirchner and Alempijevic, 2012, Kirchner et al., 2011]. It is important to note here that a robot is defined as an intelligent machine capable of 1) sensing the world around it, 2) deriving an action plan from this information in conjunction with some held knowledge, and 3) enacting this plan. Robots are often envisioned as embodied agents (appear somewhat human like), however, embodiment is not a prerequisite and the principles of robotics hold for disembodied systems (such as we demonstrated in [Caraian et al., 2015]). Through this work, we have demonstrated that robots, embodied or otherwise, can leverage sociocontextual cues and the inherent paradigm of HRI to influence behaviour.

Specifically, the above interactions leveraged a paradigm of HRI we devised and proposed in [Kirchner and Alempijevic, 2012]. This Robot Centric HRI paradigm builds on paradigms of HRI and Human-Computer Interaction (HCI); such as those discussed by Dautenhahn [Dautenhahn, 2007], Groom [Groom, 2008] and Ju [Ju and Leifer, 2008]. The Robot Centric paradigm creates a communication feedback loop between humans and robots through the introduction of new communication branches into HRI. As a result, robots are positioned as interaction peers with increased agency and the ability to lead interactions. Increasing suitability for situations in which the human may be naïve to and/or unsuspecting of the robot's goal(s); for example, public transport passengers may be unsuspecting that a robot is attempting to influence their passage, or naïve to where it is directing them.

However, there are a number of prevalent factors that interplay with influence in situ in public spaces such as train stations. For instance, consider the likely egress path influencing outcome for a 'Business Person' (already has a predetermined egress path identified, and is conscious of time) versus a 'Tourist' (unclear on best egress path, less conscious of time); clearly a different influence strategy seems appropriate for each. For example, information highlighting that the next service has been delayed and so the typically 'slower' alternative is 'faster' today seems likely to resonate with the 'Business Person', whereas information highlighting the 'easy' and 'scenic' way seems likely to resonate with the 'Tourist'. Furthermore, consider the case where options such as the above are not available but influence is highly desirable. In this case 'very strong' influence may be used with the 'Business Person' to ensure compliance, however, for 'Tourists' such 'strong' influence may potentially cause over-influence (the resultant outcome is considerably beyond the operator's intention, e.g. send people past the target) or rejection along with the subsequent dissatisfaction (refusal to comply e.g. "because it was rude").

In such, to increase a robot's effectiveness at achieving its task(s), particularly in such scenarios, a key addition of the Robot Centric paradigm is the ability to deliberately set a robot's level of interactivity (the potential of the robot to exhibit causal behaviour, that is, respond in reaction to interaction with a human [Bartneck and Forlizzi, 2004]): depending on the design of the paradigm branches and implementation, different levels of robot interactivity can be achieved. In the context of the Robot Centric HRI paradigm, a robot's interactivity is its ability to moderate the sociocontextual cues it issues based on the behavioural information it reads from humans. This is in contrast to traditional HRI paradigms, which typically positioned robots as task completers, or tools which simply completed a task when given a human command [Groom, 2008].

The Robot Centric HRI paradigm is a potentially suitable model to deliberately set, and subsequently exploit, this robot interactivity to achieve more predictable and effective influence. However, due to our piecemeal exploration of the paradigm thus far, the concept of interactivity via the paradigm has been proposed but holistically testing in situ (within the train station application space) has not been the focus, nor has its usefulness to train operators. Although, we theorise that the more interactivity a robot has through the paradigm, the more it will be able to operate as an interaction peer to effectively achieve its goal(s).

Thus, three key questions arise: Is it actually feasible 1) for the robot to self derive passenger meaningful demographics information in real time in order to drive the most appropriate influencing strategy? 2) to responsively influence people's movement behaviour in congested train stations during operations? 3) to exploit the Robot Centric HRI paradigm to increase the effectiveness of (robot) influence through shaping its interactivity? This paper presents an exploration of these questions via a robotic system that is responsive to real time person behaviours and operator's needs. Specifically, details of our methods for identification of individual passengers into demographic groups and passenger egress influencing are presented along with results from two studies. The first study was conducted at Townhall Station Sydney and explored our robotic system's ability to reliably identify the passenger demographic of individual passengers in real time. The ability of our robotic system to influence real time egress of reaxl in-transit passengers in situ, and the ability to responsively moderate influence-objective based on an observed characteristics was explored in the second study which was co-located at Perth Station Perth and the University of Technology Sydney. Finally, this paper discusses how this predictable influence of passenger egress can potentially be leveraged to benefit operations.

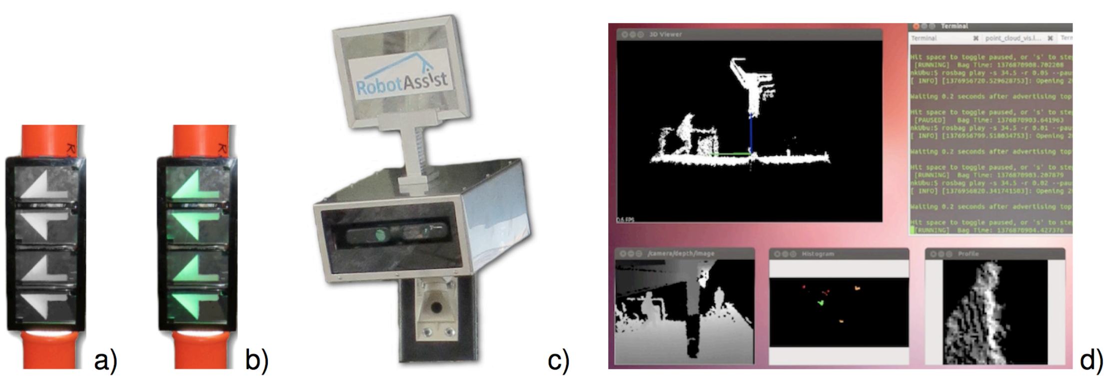
2. Foundations for Robot Lead Egress Influence

Robot interactivity, as framed by our Robot Centric HRI paradigm [Kirchner and Alempijevic, 2012], is the ability of the robot to proactively *Read*, then moderate its *Elicit* strategy based on self derived information and known behaviour-to-meaning mappings in such a way as to increase the likelihood of achieving its desired outcome(s). In order to investigate this relationship between robot interactivity and ability to influence, it is first necessary to understand interactivity, and how different levels of interactivity are necessary and can be achieved using the Robot Centric HRI paradigm. This begins with an understanding of the paradigm and the two additional feedback branches it adds to traditional HRI.

2.1 Read Information

The *Read* branch of the Robot Centric HRI paradigm sees the robot able to sense behavioural cues displayed by the interacting human(s), including non-verbal cues. This information can then be interpreted through the robot's contextual understanding and through human behaviour-to-meaning mapping available from the fields of Psychology and Behavioural Science in order to derive an action plan. One cue set rich in interaction-context knowledge when *Read* is that of person movement-location. For example, such information can reveal where a person is headed and at which point an interaction should be instantiated to maximise the likelihood of potentially influencing; the Social Interaction (proxemics) Zone (*~1.2–4.5m*), is where a majority of interactions occur and where issued cues are most salient to people, [Hall, 1966, Farenzena et al., 2009, Marquardt and Greenberg, 2012, Caraian and Kirchner, 2014a].

Figure 1: Our influencing device – shown in a) Static and, b) Dynamic/Responsive. Our SHP for robust people awareness – shown in c) & d)



The base cue that was *Read* during this study was that of people's presence-movement-location, which was then utilised to *Read* a number of different participant behaviours depending on the paradigm implementation. In the study Part 2 implementation, *Read* was achieved via Wizard-of-Oz (a.k.a. Teleoperation). In the Part 1 & 3 implementations, a previously developed person detection and tracking system [Hordern and Kirchner, 2010, Kirchner et al., 2012, Kirchner et al., 2014] was implemented on our sensing hardware platform (SHP). Our SHP, which has been devised, developed and empirically evaluated, is shown in Fig. 1c). Our SHP was demonstrated to be capable of robust people detection, tracking, and counting system in public spaces such as train stations [Kirchner et al., 2014].

2.2 Elicit Behaviour

The second additional branch of the Robot Centric HRI paradigm, *Elicit*, indicates the ability of the robot to surreptitiously present human-interpretable cues to an interaction partner in order to *Elicit* particular behavioural responses, for example to influence behaviour and/or decision making. The selection of an intended-application-space appropriate cue (that is, a cue which is sociocontextual – dependent on the application-space's social-interaction-space and contextual-task-space in order to be interpreted) is vital for effective *Elicit*, [Kirchner et al., 2011, Kirchner and Alempijevic, 2012, Caraian and Kirchner, 2013b].

Directional indicators were identified as appropriate sociocontextual cues for use in this study. There are a number of characteristics known to moderate the effectiveness of such indicators in influencing behaviour, with greater effectiveness being achieved when the indication is strong, unambiguous, and successfully attracts people's attention [Reason, 2002]. Two key characteristics are change (e.g. flashing) and colour [Bullough and Skinner, 2013, Wickens and Hollands, 2000]. Firstly, flashing lights have been shown to be more conspicuous than constant lights [Gerathewohl, 1953, Vos and Van Meeteren, 1971], as well as significantly increasing compliance with direction [Nevo et al., 2010]. A frequency in the range of *2–5Hz* results in greater noticeability [D'Egidio et al., 2014, Scadding and Losseff, 2011]. Colour and symbols can similarly affect the conspicuousness and meaning of directional indicators. By drawing on populations' colour stereotypes, colours' established symbolic meanings can be exploited. In Western cultures, for example, green and arrow symbols typically signal 'go', 'good' or safety, or direct movement in a certain direction [D'Egidio et al., 2014, Wickens and Hollands, 2000]. In order to issue cues with the above characteristics, an influencing device was designed and built for use in this study, Fig. 1a) & b). The device consists of an array of perspex screens, each with arrows etched into them. The levels of interactivity designed for this device were:

Static – As can be seen in Fig. 1a), the device appears inactive in Static mode. However, the etched perspex arrows are clearly visible – the information appears fixed and unchangeable.

Dynamic – In Dynamic mode, Fig. 1b), internal illumination gives the effect that green arrows are being displayed on screens – the information appears potentially changeable.

Responsive – A Responsive system is achieved through leveraging the psychological and behavioural trigger of an event congruent with physical entry into the Social Interaction Zone, which is known to evoke the perception of entering an interaction (Section 2.2 and [Hall, 1966]). Specifically, while a person is in the Public Zone, the device remains in Dynamic mode. The device issues a sociocontextual cue upon the person social trigger of Social Interaction Zone entry. A flashing frequency of *4Hz* was selected.

2.3 Interactivity

Through employing the *Read* and *Elicit* branches of the Robot Centric HRI paradigm described above, different levels of robot interactivity can be achieved. For example, a traditional task completer robot has low interactivity: without the ability to *Read*, such a robot is inherently unable to moderate its *Elicit*, and hence is only able to carry out a single type of *Elicit*. That is, its *Elicit* remains static.

In the previously mentioned salient-object handover study, on the other hand, the robot had a higher level of interactivity: through *Read*ing person location, the robot was able to physically direct its cues towards the intended recipient [Kirchner and Alempijevic, 2012]. Even greater interactivity was achieved during the interaction initiation study through *Read*ing both person presence within the Social Interaction Zone, and the position of the person. This enabled the robot to issue its cues at the appropriate time to influence the passerby to enter into an interaction, in one case responsively issuing cues as the participant approached the robot [Kirchner and Alempijevic, 2012].

These examples suggest that the level of interactivity of the robot relates to the effectiveness of its influence, where effectiveness is considered to be the ability of the robot to target its influence to achieve specific desired outcome(s). Furthermore, It is known that user-group demographics reveal insights into probable behaviours and responses to circumstances; marketing and advertising leverages this phenomenon to achieve particular ends [Sheth, 1974]. Furthermore, movement characteristics such as walking path and speed have been identified as indicators, and have been demonstrated robustly observable in real world situations [Kirchner et al., 2014].

In public spaces such as transport environments, Passenger Information (PI) systems incorporate some or all of the above characteristics, resulting in a range of fidelity and interactivity. Presently, Static and Dynamic PI systems are ubiquitous. At the information communications level, information appears to the viewer as being fixed and not readably changed in Static PI systems. Dynamic PI systems' information appears to the viewer as potentially changeable from a limited set of information. Static and Dynamic PI systems map to the traditional paradigm for HRI described in [Kirchner and Alempijevic, 2012], where the robot assumes the passive role of task completer.

However, as demonstrated by the Robot Centric HRI paradigm, opportunity exists to change the fundamental paradigm for interaction via PI systems and to leverage psychological and behavioural triggers to increase their interactivity, thus making PI systems more responsive to individual passenger's demographic and current operations information, and drawing passengers into a rich and highly salient bi-directional targeted-information interchange. That is, to develop Responsive Passenger Information Systems (R-PIS) capable of pursuing regularly changeable multiple influence-objectives.

3. Empirical Explorations

To explore this, different Robot Centric HRI paradigm implementations were designed to achieve various levels of interactivity and to test the robot's ability to self derive meaningful passenger demographic information. These implementations were realised in a disembodied robot. This robot was two-part: a sensing and computational component, and an actuation component. Each of the paradigm implementations were designed with successive activation of the *Read*-*Elicit*-*Read* branches. Interactivity was regulated by moderating the attributes of each of these branches. An isolated instance of the *Read* branch for *Read*ing persons' movement-location was the focus of Part 1 of the study; where the robot's ability self derive passenger demographic information from this movement-location data was explored (described in Section 3.1).

In the paradigm implementation for Part 2 of the study (described below in Section 3.2), the first *Read* was of both person presence in the Public Zone (initial robot setup can be carried out as the interaction has not commenced), and whether said person had entered the Social Interaction Zone (cue issuance should be triggered). Three cues were available for random selection for issuance in *Elicit*: Static, Dynamic, and Responsive (detailed in Section 2.2). The final *Read* was of the participants' change in movement. The paradigm implementation for Part 3 of the study (Section 3.3) built on the Part 2 implementation with the key addition of a *Read* of the person's entry position into the Social Interaction Zone; enabling the cues issued in *Elicit* to be moderated based on this behavioural information in order to attempt to increase the likelihood of achieving the goal – i.e. increased interactivity. The final *Read* was again of the participants' change in movement. This enabled exploration of multiple influence-objectives dependent on a *Read* passerby characteristic. A three-part empirical exploration was conducted (total *n=641*) carried out in two separate major public train station (*n=368 + 84 + 105*) and a university (*n=84*); we hypothesised:

H1 – A passenger's demographic can be autonomously determined through analysis of in public space observations of their movement behaviour and characteristics.

H2 – It is feasible to influence people's movement behaviour in public spaces using the Robot Centric HRI paradigm.

H3 – Increasing a robot's interactivity via the Robot Centric HRI paradigm will result in an increase in the effectiveness of its ability to influence; that is, its ability to target its influence to achieve specific desired outcome(s).

From these we predict:

P1 – Statistical clustering of empirically acquired movement behaviour and characteristics from passengers in a train station will reveal distinct groups consistent with those identified via anthropological investigation.

P2 – Passenger information systems utilising the Robot Centric HRI paradigm will have greater influence on participants than those utilising the traditional HRI paradigm.

P3 – *Read*ing an additional behavioural cue will yield insights useable to moderate *Elicit* to increase the effectiveness of the robot's influence.

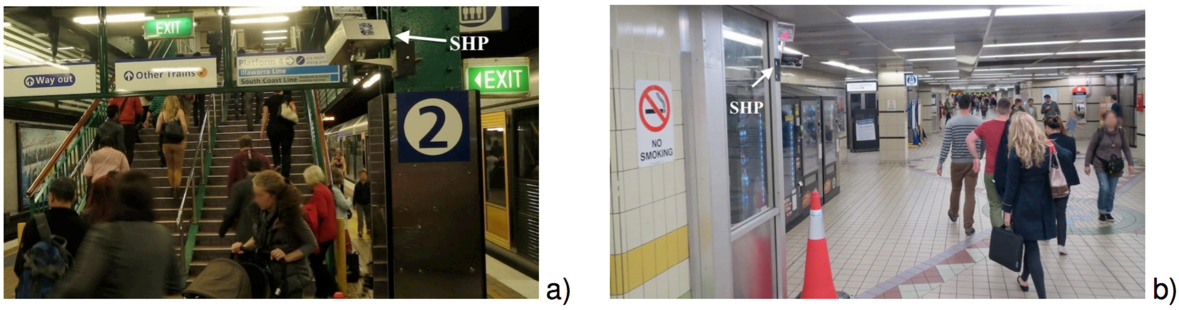
3.1 Part 1 – Self Deriving Passenger Demographics

To explore the feasibility of autonomously placing newly detected passengers within defined user-groups we conducted a field study with commuters at a major public train station; Townhall in Sydney, Australia. A preliminary anthropological observations based investigation was first conducted over several hours by two experimenters at the proposed field study site. From this three user-groups were defined. Subjectively termed as: *Business People* – who tended to walk relatively quickly with a straight path, *Tourists* – who tended to walk relatively slowly with highly irregular paths, and *Normal Passengers* – who's speed and path characteristics lay between *Business People* and *Tourists*. The subsequent field study explored the feasibility of our SHP autonomously observing passengers movement characteristics, and classifying passengers into these groups. This field study is detailed in the follow sub sections.

3.1.1. Participants & Setting

There were *368* participants randomly selected and directly measured by our SHPs in various locations around the station – *282* from three similar thoroughfare locations on a platform and *86* from a single thoroughfare location in the main concourse. They were typical rail commuters. There was no remuneration for participation nor effort to recruit participants. We used the SHP device described in Section 2, Fig.1c). The device is approximately *250mm* x *250mm* x *100mm*, resembles a security camera, and was mounted to infrastructure at approximately *2.2m* (shown in Fig. 2). The experiment was staged in Townhall Station Sydney, Australia. Studies were conducted at four locations within the station. Platform Locations: three thoroughfare locations were elected on a single platform, and one of these locations is shown in Fig.2a) as a typical example. The remaining location was in a thoroughfare in the main concourse (shown in Fig.2b). As can bee seen from the figure, in both cases the SHP was mounted unobtrusively to the infrastructure.

Figure 2: Setting for the study a) One platform location and, b) The main concourse location



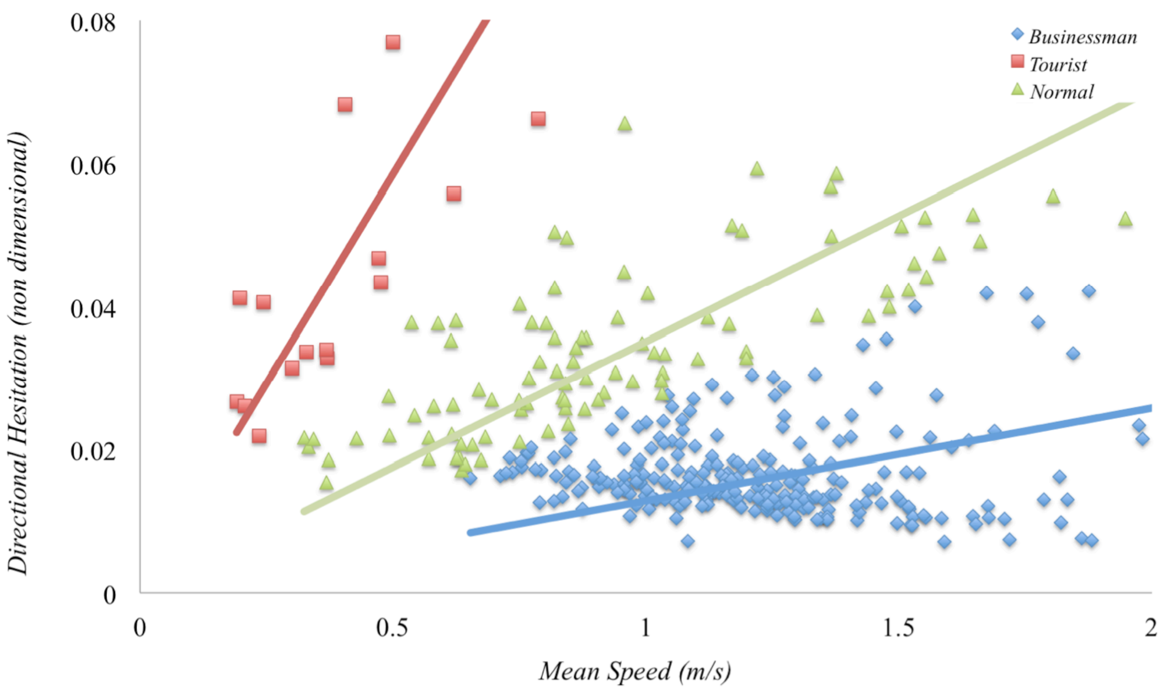
3.1.2. Procedure & Measurement

The SHP was installed onto the infrastructure and then set to detect, track and log passersby and left unattended to do so for approximately one hour. This was repeated at the four aforementioned locations. The co-ordinate positions of all detections of each person were autonomously logged by the SHP. Each person typically would have between *20–50* logged positions (depending on their walking speed) as they passedby the SHP. This series of logged person-specific co-ordinate positions constituted the persons path.

3.1.3. Results

Paths from the *368* detected and tracked passengers were analysed with two measures representing each person extracted; their *Mean Speed* $(M_s = \overline{(\sqrt{\delta x^2 + \delta y^2})/\delta t})$ and a non-dimensional number encapsulating their magnitude and frequency of changes in direction (*Directional Hesitation* $= |\overline{|\delta\delta x/\delta t|}/M_s| + |\overline{|\delta\delta y/\delta t|}/M_s|$). *The k-means* statistical clustering method using cosine distance was conducted on this measure set; the resulting statistically valid clusters are shown in Fig. 3. Importantly, no significant cluster shape variation was detected between the data from the four locations, suggesting station wide consistency in behaviour.

Figure 3: The three anthropologically identified user-groups evident in *k-means* statistical clustering of the empirical measures



These results demonstrate that the user-groups defined through the preliminary anthropological investigation were autonomously observable and statistically valid. K-means statistical clustering identified three statistically valid robust clusters indicating behaviour consistency between locations within the station, and with the anthropologically observed clusters. This provides support for our *H1/P1* that passengers' user-group demographic can be autonomously determined from in situ observations of walking characteristics.

3.2 Part 2 – Influence in a Public Space

In order to evaluate the effect of the previously described influence, we first conducted a field study with commuters at a major public train station; Perth Station in Perth, Australia. As commuters moved within the train station, one of three levels of information systems – Static, Dynamic, and Responsive PI systems – attempted to influence their behaviour, and the subsequent effect was measured. The focus of this part of the study was on addressing *H2*, however *H3* was also preliminarily explored. The following sub-sections describe the participants, experimental design and procedure, evaluation measures and hypotheses.

3.2.1. Participants & Setting

There were *189* participants randomly selected and directly measured from a larger total number of passersby – *84* in Location 1 and a further *105* in Location 2. They were typical rail commuters. There was no remuneration for participation nor effort to recruit participants. We used the influencing device shown in Fig. 1a) and Fig. 1b), as depicted in Fig. 4. The experiment was staged in Perth Central Station – a major public train station in Perth, Australia. Studies were conducted at two locations within the station. Location 1: a long public thoroughfare corridor (shown in Fig. 4a), and Location 2: a blind corner subject to passenger flow cross over (shown in Fig. 4b). As can bee seen from the figure, in both cases the influencing device was placed at roughly the thoroughfare midpoint.

Figure 4: Setting for the Part 2 study a) Location 1 and, b) Location 2

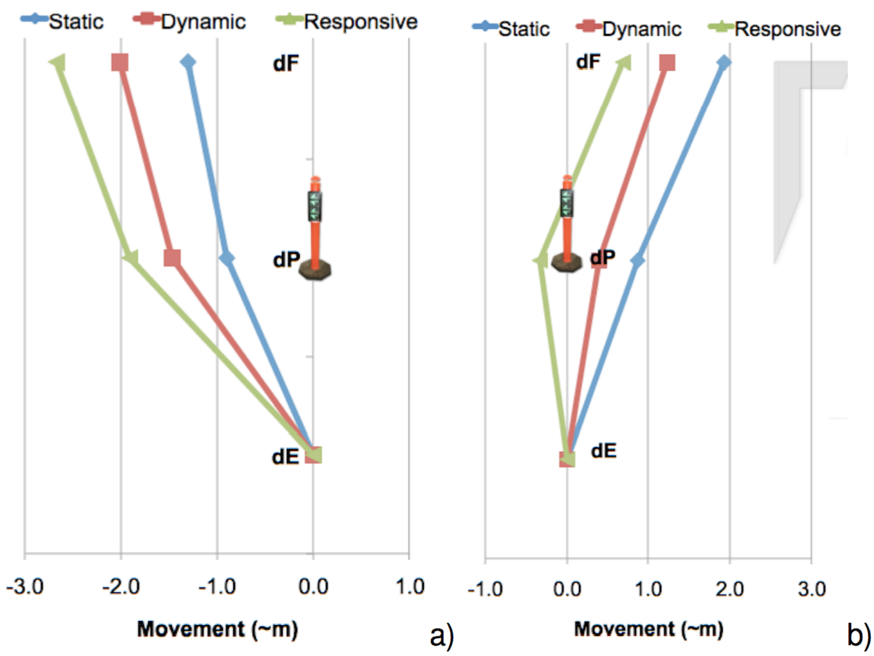
a)

b)

3.2.2. Procedure & Measurement

The study was designed with three levels of information systems – Static, Dynamic, and Responsive – which were implemented as described in Section 2.2. All other acts/cues were consistent throughout the trials. A Wizard-of-Oz study was constructed. The influencing device was cycled through the three levels of information system, with *4* independent trials conducted at Location 1 (total of *84* trials) and *5* each at Location 2 (total of *105* trials) at each level. Each trial commenced with the influencing device being reset, and a commuter passerby being randomly selected by the experimenters. In the case of Responsive the experimenters tracked the passerby and triggered the influencing device's cue as the passerby crossed into the Social Interaction Zone. Participants' change in distance from their originally measured position, and relative to a zero-axis which was parallel to the passage and ran through the influencing device was used as the measure, as shown in Fig. 5. Three repeated measures were taken for each participant. The first, at the **E**ntry point of the Social Interaction Zone relative to the influencing device. The second, at the **P**ass point of the influencing device, and the third, at the **F**inal measure point which was the exit point of the influencing device's Social Interaction Zone.

Figure 5: Influencing people leftwards at a) Location 1 and, b) Location 2



3.2.3. Results

A total of *84* trials (*28* trials for each of Static, Dynamic, and Responsive) were conducted at Location 1 and a total of *105* trials (*35* trials for each of Static, Dynamic, and Responsive) were conducted at Location 2; *3* repeated measures were taken in each trial. A relatively steady stream of commuters flowed past during the trials, and approximately *5* commuters passed by per *1* selected to facilitate a trial. The experimenters did not attempt to control the number of participants or observers for the trials, and participants were randomly selected.

Figure 5 shows the average of the three repeated measures for the Static, Dynamic, and Responsive cases at Location 1 and 2. A mixed design ANOVA was performed for each location. The within subject main effect for the *3* measure points was significant in Location 1 and 2, $F=67.64$, $p<0.001$ and $F=99.43$, $p<0.001$ respectively. The between subject main effect for the *3* levels was also found significant in Location 1 and 2, $F=259.44$, $p<0.001$ and $F=49.60$, $p<0.001$ respectively. Pairwise comparisons were conducted between the *3* levels. Significant differences were found between Static and Dynamic (Location 1 – *mean difference* = *0.63m*, $p=0.018$, Location 2 – *mean difference* = *0.54m*, $p=0.05$), Static and Responsive (Location 1 – *mean difference* = *1.18m*, $p<0.001$, Location 2 – *mean difference* = *1.175m*, $p<0.001$), and Dynamic and Responsive (Location 1 – *mean difference* = *0.55m*, $p=0.039$, Location 2 – *mean difference* = *0.64m*, $p=0.017$). Pairwise comparisons also revealed significant differences between the **P** and **F** measure points (Location 1 – *mean difference* = *0.56m*, $p<0.001$, Location 2 – *mean difference* = *0.94m*, $p<0.001$); relative to measure point **E**. These results support our hypothesis (*H2*) – that people's movement behaviour in public spaces can be influenced using the Robot Centric HRI paradigm. Specifically, participants' deviation was found to be statistically in the direction of intended influence as they moved towards and past the influencing device in both Location 1 ($F=67.64$, $p<0.001$) and Location 2 ($F=99.43$, $p<0.001$). The significant movement between the **P** and **F** measure points (Location 1 – *mean difference = 0.56m*, $p<0.001$, Location 2 – *mean difference = 0.94m*, $p<0.001$) relative to measure point **E** suggests an ongoing influence effect.

Further, the influence effectiveness was significantly different between the three levels in Part 2 of the study (Static, Dynamic, and Responsive) in both Location 1 ($F=259.44$, $p<0.001$) and Location 2 ($F=49.60$, $p<0.001$), with Dynamic significantly more effective than Static (Location 1 – *mean difference = 0.63m*, $p=0.018$, Location 2 – *mean difference = 0.54m*, $p=0.05$), and Responsive significantly more effective than Dynamic (Location 1 – *mean difference = 0.55m*, $p=0.039$, Location 2 – *mean difference = 0.64m*, $p=0.017$). This demonstrates, as per prediction *P2*, that passenger information systems utilising the Robot Centric HRI paradigm (Responsive) will have greater influence on participants than those utilising the traditional HRI paradigm (Static and Dynamic). These results suggest that the Robot Centric HRI paradigm enabled R-PIS was most able to influence participants into conforming to its suggestions. This provides partial support for hypothesis *H3* that increasing levels of robot interactivity (from Static to Dynamic to Responsive) will result in an increase in the effectiveness of its influence.

3.3. Part 3 – Robot Interactivity and Influence Effectiveness

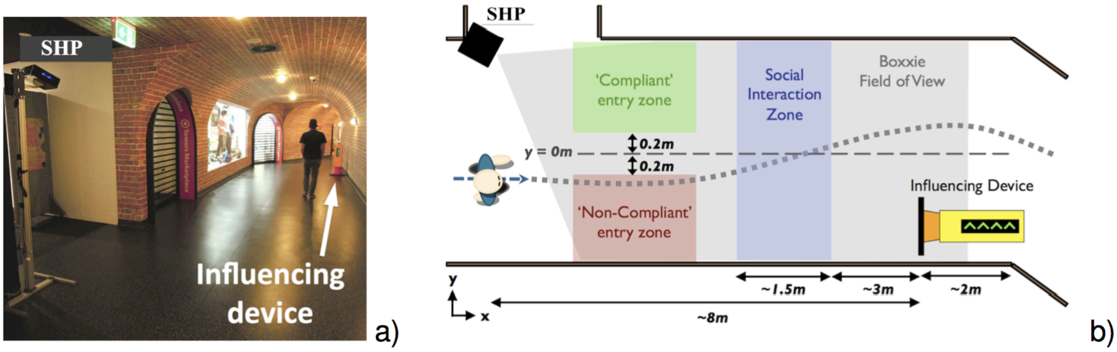
Part 3 of the study focused on more deeply exploring *H3*. A field study was conducted with passersby in a university food court. As the passersby approached the influencing device, the information system presented as either Static or Responsive, depending on the passerby's initial behaviour, and attempted influence. The subsequent effect was measured. Part 2 findings were also reproduced in order to verify that the result was still valid in the different setting. The following sub-sections describe the participants, experimental design and procedure, evaluation measures and hypotheses.

3.3.1. Participants & Setting

Participants ($n=84$) were randomly selected passersby to the experiment location who were traveling towards the influencing device; no particular demographic was evident. There was no remuneration nor effort to recruit participants. The experiment was staged in a long straight corridor with a blind corner in the university food court. This setting is shown in Fig. 6a), which presents a snapshot taken during the period of the experiment. The influencing device was positioned *~2m* in front of the corner and against the right hand wall, from the point of view of the participants' approach direction. Our SHP was located *~8m* from the influencing device on the opposite wall of the corridor, with its field of view directed out towards the influencing device. Figure 6b) shows a diagrammatic representation of the setting in which the positions of our SHP and the influencing device are shown, along with our SHP's field of view.

Unbeknownst to participants, there were two entry zones into the experiment, which are also depicted in Fig. 6b). Participants who entered the experiment area on the left hand side of the corridor were termed to be initially 'Compliant' (C) with the desired influence behaviour. Participants on the right side of the corridor, on the other hand, were termed 'Non-Compliant' (NC). Participants who were moving down the center of the corridor between these two zones (−0.2m – 0.2m) were considered neither C nor NC and were excluded.

Figure 6: The Part 3 study setting and setup; shown in a) and b) respectively



3.3.2. Procedure & Measurement

There were two cases for the robot-issued cue – Responsive and Static. These cases were randomly counterbalanced with the C and NC participants: in some trials the Static information system was presented to C participants and the Responsive cue was presented to NC participants, whilst in other trials this was reversed, other acts were consistent. Each trial commenced with the random selection of a case, and began when a participant walking down the corridor was detected by our SHP as having entered the Public Zone and was *Read* as either C or NC, depending on which entry zone they were located in; as shown in Fig. 6b). Depending on the case, the influencing device was set to either Static or Responsive. The participant's position was subsequently tracked via our SHP, and, in the Responsive case, the influencing device's cue was triggered as they crossed into the Social Interaction Zone. As in Part 1, the participants' change in distance from their originally measured position, and relative to a zero-axis which was parallel to and in the center of the corridor, was used as the measure. As the participants would have had to move in the negative direction to cut the corner, and the positive direction was in line with the attempted influence direction, a less negative change in distance equated to greater influence. Two measures were taken for each participant. The first at the **E**ntry point of the Social Interaction Zone relative to the influencing device. The second at the **F**inal detection point – at which they passed out of the range of the person detection system – which was approximately *1m* past the influencing device.

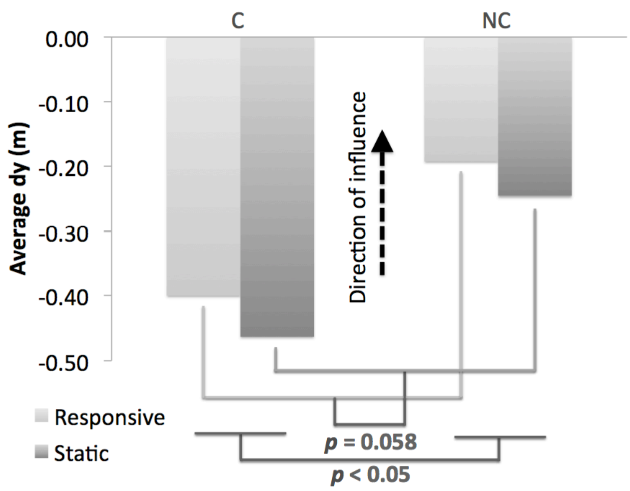
3.3.3. Results

In total, *100* trials were conducted. Trials in which the participant was lost by the person detection system before reaching the influencing device were not considered in the results, leaving *84* trials for analysis. There were *56* C and *28* NC participants. A total of *~2,700* person location readings were autonomously logged during the experiment, with an average of *~32* person location readings logged per trial. Figure 7 shows the average of the measure for C and NC participants in the Static and Responsive cases. A two way ANOVA revealed a significant main effect between C and NC participants, $F=1{,}614.91$, $p<0.05$, *mean difference* $= 0.21m$, and a borderline significant main effect between Static and Responsive cases, $F=121.02$, $p=0.058$, *mean difference* $= 0.058m$. The interaction effect was not significant. Prediction *P2* was further supported by these results (which first reproduced the results from Part 2 in order to verify the findings). Specifically, Responsive was found to result in borderline significant greater influence compared to Static ($F=121.02$, $p=0.058$, *mean difference* $= 0.058m$). The borderline result is potentially due to the exclusion of participants who were neither C nor NC (i.e. in the center of the corridor).

These results provide support for prediction *P3* that *Read*ing an additional behavioural cue will yield insights useable to moderate *Elicit* to increase the effectiveness of the robot's influence (in Part 3 of the study, an additional *Read* of the participant's entry position into the

Social Interaction Zone). Specifically, a significant difference was found between the influence on C and NC participants (*F=1,614.91, p<0.05*), with NC participants influenced an average of *0.21m* more than C participants. This result has implications for the design of *Elicit* influence strategies. For instance, consider the case where 'too much' influence may have a negative repercussion. The robot, in that case, may refrain from presenting *Elicit* cues to 'more influenceable' people observed to be already near this threshold.

Figure 7: Influence reducing the extent of people cutting the corner



4. Conclusions and Future Work

The empirical results presented in this paper provide support for our three hypotheses and our predictions. In Part 1 study, we focused on quantitively validating the findings from an anthropological observations based investigation which defined three user-groups of application-space meaning. A field study was conducted in four locations in a major Australian public train station in which participants (*n=368)* were autonomously detected and tracked by our SHP. We found that measures autonomously extracted from empirically acquired data resulted in reliable and statistically valid robust clusters indicating behaviour consistency between locations within the station, and that were consistent with those identified anthropologically. Thus showing the feasibility of autonomously extracting behavioural indicators from observation and mapping these indicators to higher-levels of meaning; in this case user-group demographics. The results demonstrate the feasibility of robust real-time autonomous passenger user-group demographics classification down to the individual passenger level.

In Parts 2 & 3 of this study, we focused on quantitively investigating whether increasing a robot's interactivity (that is, its ability to *Read* behaviour, then moderate its *Elicit* strategy based on this information and known behaviour-to-meaning mappings) will result in an increase in the effectiveness of its influence (i.e. its ability to target its influence to achieve specific desired outcome(s)). A two-part study (total *n=273*) was conducted in both a major Australian public train station (*n=84 + 105*) and a university (*n=84*). Passersby were exposed to a robot designed to influence their passage, which had various levels of interactivity. The results demonstrated that the influencing device's use of the Robot Centric HRI paradigm to enable a R-PIS, saw it most able to influence participants into conforming to its suggestions and highlighted nuances of the interplay between interactivity and influence.

Considering the results holistically, we found that an increase of the robot's interactivity led to a multi facetted view of the robot's ability to influence, in this case the passage deviation of passersby. The intricacies of these findings have implications for HRI in this target application space. For instance, in the pursuit of achieving operator's goals it may not always be the appropriate course of action to design for maximum influence as over-influence or rejection may occur. For instance, if relatively small movement deviation is desired then a strategy utilising less influence may be employed as too much influence may have an undesired effect such as sending the passenger past the goal; which when recognised by the passenger increases the likelihood of future rejection. Or similarly, if a passenger is identified as a Business person the system may pursue a different influence strategy and present entirely different information to achieve its goal than if that passenger were a Tourist; e.g. information pointing to the next service versus information pointing to a local tourist attraction - both of which intend to redirect that passenger's egress. This interplay between levels of interactiveness and information delivery modes guided by self derived knowledge generated in situ and in real time provides the underpinnings for supporting multiple operator derived multiple influence-objectives with the feasibility to change regularly; i.e. R-PIS.

The importance of the findings presented here within is in that they evidence the feasibility of, and give shape to, a R-PIS that is capable of proactively, and in real time, identifying meaningful attributes of a passenger with which information delivery is desirable and then exploiting these attributes to most effectively communicate operator's objective - to the point of influencing said passenger's behaviour. These findings promise the resulting R-PIS usefulness for daily operations where potentially multiple influence-objectives which change regularly, exists; as opposed to static egress influencing devices such as barriers.

Limitations – That presented has a number of limitations, the most pressing perhaps being that this study lacked an exploration of habituation to the influencing device and the subsequent effect on its ability to influence in actual congested train stations. Additionally, measurement inaccuracies potentially occurred, and differences in behaviour between male and female participants were not accounted for. Despite these limitations, however, the results of this study suggest there is value in increasing the interactivity of robots via the Robot Centric HRI paradigm, and furthermore – by increasing robots' ability to *Read* behavioural cues and utilise behaviour-to-meaning mapping to moderate their *Elicit* strategies, the ability of the robot to target its influence to achieve specific desired outcome(s) can be greatly increased.

Future work will focus on further investigating the interactivity of robots, particularly other behavioural cues the robot could *Read* to more intelligently moderate its *Elicit* strategy in situ in congested train stations. For example, an understanding of where participants gaze is directed can enable the robot to communicate intentionally to people in the environment through an understanding of where people's attention is directed (as discussed in [Caraian and Kirchner, 2014b]). Additionally, the effect of commuter habituation on a robot's ability to influence will be explored.

Acknowledgments

The IP contained here within is Patent Pending [Kirchner, 2012a, Kirchner, 2012b, Kirchner, 2015]. This work is supported by UTS' Centre for Autonomous Systems and RobotAssist (*www.robotassist.org*). Further information on our activities is available at *www.nkHRI.com*

References

[Bartneck and Forlizzi, 2004] Bartneck, C. and Forlizzi, J. (2004). A Design-Centred Framework for Social Human-Robot Interaction. In *Ro-Man*, pages 591–594.

[Bullough and Skinner, 2013] Bullough, J. and Skinner, N. (2013). Influence of Visual Signal Flash Intensity and Duration on Perception. In *Suppression, Detection, and Signaling Research and Applications Symposium (SUPDET)*, pages 1–5.

[Caraian and Kirchner, 2013a] Caraian, S. and Kirchner, N. (2013a). Incidental Robot Gaze Behavior Inadvertently Influencing Choice. In *HRI '13: Proceedings of the 8th ACM/IEEE International Conference on Human-Robot Interaction*, pages 1–2.

[Caraian and Kirchner, 2013b] Caraian, S. and Kirchner, N. (2013b). Influence of Robot-Issued Joint Attention Cues on Gaze and Preference. In *HRI '13: Proceedings of the 8th ACM/IEEE International Conference on Human-Robot Interaction*, pages 95–96.

[Caraian and Kirchner, 2014a] Caraian, S. and Kirchner, N. (2014a). Head pose behavior in the human-robot interaction space. In *in HRI '14: Proceedings of the 9th ACM/IEEE Int. Conf. on Human-robot interaction*, pages 132–133, New York, New York, USA. ACM Press.

[Caraian and Kirchner, 2014b] Caraian, S. and Kirchner, N. (2014b). Head Pose Behavior in the Human-Robot Interaction Space. In *HRI '14: Proceedings of the 9th ACM/IEEE International Conference on Human-Robot Interaction*, pages 132–133.

[Caraian et al., 2015] Caraian, S., Kirchner, N., and Colborne-Veel, P. (2015). Moderating a robot's ability to influence people through its level of sociocontextual interactivity. In *HRI '15: Proceedings of the 10th ACM/IEEE Int. Conf. on Human-Robot Interaction*, pages 149–156.

[Dautenhahn, 2007] Dautenhahn, K. (2007). Socially intelligent robots: dimensions of human– robot interaction. *Philosophical Transactions*, 362:679–704.

[D'Egidio et al., 2014] D'Egidio, G., Patel, R., Rashidi, B., Mansour, M., Sabri, E., and Milgram, P. (2014). A study of the efficacy of flashing lights to increase the salience of alcohol-gel dispensers for improving hand hygiene compliance. *J Infect Control*, 42:852–855.

[Farenzena et al., 2009] Farenzena, M., Tavano, A., Bazzani, L., Tosato, D., Paggetti, G., Menegaz, G., Murino, V., and Cristani, M. (2009). Social interactions by visual focus of attention in a three-dimensional environment. In *Workshop on Pattern Recognition and Artificial Intelligence for Human Behaviour Analysis (PRAI*HBA)*, volume 30, pages 115–127.

[Gerathewohl, 1953] Gerathewohl, S. (1953). Conspicuity of Steady and Flashing Light Signals: Variation of Contrast. *J. Opt. Soc. Am. (JOSA)*, 43(7):567–568.

[Gray, 2013] Gray, J. (2013). Rail simulation and the analysis of capacity metrics. In *Australasian Transport Research Forum Proceedings*, number October, pages 1–15.

[Groom, 2008] Groom, V. (2008). What's the best role for a robot? Cybernetic models of existing and proposed human-robot interaction structures. In *Proceedings of the Int. Conf. on Informatics in Control, Automation, and Robotics (ICINCO)*, Funchal, Portugal.

[Hall, 1966] Hall, E. (1966). *The Hidden Dimension*. Doubleday.

[Hordern and Kirchner, 2010] Hordern, D. and Kirchner, N. (2010). Robust and Efficient People Detection with 3-D Range Data using Shape Matching. In *Proceedings of the 2010 Australasian Conference on Robotics and Automation*.

[Ju and Leifer, 2008] Ju, W. and Leifer, L. (2008). The Design of Implicit Interactions: Making Interactive Systems Less Obnoxious. *Design Issues*, 24(3):72–84.

[Kirchner, 2012a] Kirchner, N. (2012a). PCT Patent 2014000086 - Crowd influencing system.

[Kirchner, 2012b] Kirchner, N. (2012b). PCT Patent 2014000087 - Transport passenger guidance system.

[Kirchner, 2015] Kirchner, N. (2015). PCT Patent 2015900381 - Devices, frameworks and methodologies configured to enable automated monitoring and analysis of dwell time.

[Kirchner and Alempijevic, 2012] Kirchner, N. and Alempijevic, A. (2012). A Robot Centric Perspective on the HRI Paradigm. *Journal of Human-Robot Interaction - Special Issue on HRI Perspectives and Projects from around the Globe*, 2(1):1–23.

[Kirchner et al., 2011] Kirchner, N., Alempijevic, A., and Dissanayake, G. (2011). Nonverbal Robot-Group Interaction Using an Imitated Gaze Cue. In *HRI '11: Proceedings of the 6th ACM/IEEE International Conference on Human Robot Interaction*, pages 497–504.

[Kirchner et al., 2012] Kirchner, N., Alempijevic, A., and Virgona, A. (2012). Head-to-shoulder signature for person recognition. In *Proceedings - IEEE International Conference on Robotics and Automation*, pages 1226–1231.

[Kirchner et al., 2014] Kirchner, N., Alempijevic, A., Virgonia, A., Dai, X., Plo ̈ger, P., and Venkat, R. K. (2014). A robust people detection, tracking, and counting system. In *Proceedings of the 2010 Australasian Conference on Robotics and Automation*.

[Marquardt and Greenberg, 2012] Marquardt, N. and Greenberg, S. (2012). Informing the Design of Proxemic Interactions. *Pervasive Computing*, 11(2):14–23.

[Nevo et al., 2010] Nevo, I., Fitzpatrick, M., Thomas, R., Gluck, P., Lenchus, J., Arheart, K., and Birnbach, D. (2010). The Efficacy of Visual Cues to Improve Hand Hygiene Compliance. *Simul Healthc*, 5(6):325–331.

[Reason, 2002] Reason, J. (2002). Combating omission errors through task analysis and good reminders. *Qual Saf Health Care*, 11:40–44.

[Scadding and Losseff, 2011] Scadding, J. and Losseff, N. (2011). *Clinical Neurology*. Hodder Arnold, London.

[Sheth, 1974] Sheth, J. N. (1974). *Role of demographics in consumer behavior / 218*. [Urbana, Ill.] : College of Commerce and Business Admin., University of Illinois.

[Veitch et al., 2013] Veitch, T., Partridge, J., and Walker, L. (2013). Estimating the Costs of Over-crowding on Melbourne s Rail System. In *Australasian Transport Research Forum 2013 Proceedings*, number October, pages 1–14.

[Vos and Van Meeteren, 1971] Vos, J. and Van Meeteren, A. (1971). Visual Processes Involved in Seeing Flashes. In *International Symposium of Imperial College of London. The Perception and Application of Flashing Lights.*, pages 3–16.

[Wang and Legaspi, 2012] Wang, B. and Legaspi, J. (2012). Developing a train crowding economic costing model and estimating passenger crowding cost of Sydney CityRail network. In *Australasian Transport Research Forum Proc*, number September, pp. 1–15.

[Wickens and Hollands, 2000] Wickens, C. and Hollands, J. (2000). *Engineering Psychology and Human Performance*. Prentice-Hall, Upper Saddle River, NJ.