Research Paper

Investigating and validating methods of monitoring foot-traffic in night-time entertainment precincts in Australia

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ABSTRACT

Background: Assaults occur frequently in night-time entertainment precincts (NEPs), with rates typically reported using estimated resident population. However, this form of reporting does not accurately represent the number of people within the NEP at the time of an assault or potential fluctuations in density throughout the course of the night. As such, the aim of this study was to assess multiple methods of obtaining an accurate estimate of hourly foot-traffic within NEPs.
Methods: The validity and reliability of three types of foot traffic counters were assessed. A passive-infrared sensor and two different types of smartphone sensor were installed at two sites in Australia from 2016 to 2018, ongoing (pilot phase: 2016–2017; validation phase: 2018). Researchers also manually counted the number of people walking past through the range of two of these sensors across the course of Friday, Saturday and Sunday nights between 8 pm to 2am.
Results: Results show a similar trend between the smartphone counts, the sensor counts, and the manual counts; however there was notable variability (43%–267% compared with manual counts). Analysis showed that all measures were significantly positively correlated.
Conclusion: Reliable counting of the number of people attending nightlife precincts is an important element of ongoing studies into nightlife settings and associated rates of harm. There are multiple methods of estimating fluctuations in foot traffic within a NEP, however, determining the most appropriate method to use requires consideration of the proximity of pathways in the area, budget constraints, and project aims. Of the methods tested, laptop WiFi traffic monitoring programs functioned the least consistently. Specifically designed smartphone sensors overcame this issue; however, they required dedicated power sources. The current study found infrared scanners appeared to be the most accurate across sites; additionally they functioned consistently, and were the simplest method to setup and maintain.

Introduction

Alcohol-related harm is a widespread problem across Australia, that has significant economic impact (Manning et al., 2013). Much of this harm occurs in high-risk areas inside and around licensed venues (McIlwain & Homel, 2009) within night-time entertainment precincts (NEPs). One difficulty in conducting research in NEPs is determining an accurate rate of alcohol-related harm for those visiting the area on a given night. Currently, research in NEPs typically uses population-based injury and assault rates, with estimated residential population (ERP) as the denominator (Kypri et al., 2016; Miller et al., 2013, 2017). However, this is unlikely to accurately represent the number of persons

attending NEPs, given unpublished data shows that only 11% of nightlife patrons report their postcode of residence as within the nightlife district they are attending (Miller et al., 2013). Additionally, ERP does not take into account the dynamic influence crowding has on alcohol-related harm in NEPs, which has been associated with increased aggression (Hughes et al., 2011). Crowding is a particularly important factor, as it has been shown to independently predict police recorded assaults in and around bars, while controlling for multiple other environmental conditions (Morrison et al., 2015). The ability to consistently determine the crowdedness of a NEP over the night would overcome these measurement issues, allowing more accurate rates of assaults or injuries to be calculated, enabling exposure levels to be

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appropriately reflected, and to examine the associations between exposures of interest, and the incidence of alcohol-related harm.

One alternate method to the use of ERP is to count foot traffic in a given area through manual counting of pedestrians, however this is resource intensive, and can be difficult in busy thoroughfares. For instance, the local council in Sydney, Australia, conduct manual counts twice a year for 10 min and multiply by six to get an hourly count (City of Sydney, 2017). Another study estimated the number of people inside bars and clubs in Toronto, Canada using observers to manually count patrons (inter-rater correlation of 0.94 at peak; (Graham et al., 2006)), however this did not require them to count continuously over long periods of time as would be required to accurately determine pedestrian traffic. The use of a manual count approach only provides a snapshot of pedestrian traffic and is unlikely to provide a representative account of foot traffic on different days of the week and hour of the day. The use of sensors to count foot traffic has also been used in an attempt to address the limitations of manual counts. For example, in the city of Melbourne, Australia, laser line and infra-red technology is utilised, which counts each time a person 'breaks' a laser line (City of Melbourne, 2018). Counting the number of WiFi beacon requests from devices with unique MAC addresses in a fixed area has also been used (Li, 2016).

Foot traffic counts are used to inform policy and determine pedestrian traffic management, and if not conducted accurately have the potential to negatively impact policy choices, including the allocation and distribution of resources. A technology-based approach to people counting is recommended to overcome the limitations of manual counts. Therefore, as a part of an ongoing research programme, the current study sought to pilot and critically evaluate multiple technology-based methods of people counting within three NEPs in Australia. The study aimed to determine which counting method would be the most suitable for future research, in terms of accuracy in relation to manual counts, functionality, and ease of implementation.

Methods

A series of methods were piloted to count the number of people in three Australian NEPs between 2016 and 2018. Approaches that functioned consistently through a pilot stage were compared to manual counts for validation. This project was granted ethics approval by a University Ethics Committee.

Study sites

Three cities in Australia were used for the evaluation. The NEP in Geelong, Victoria was used in both the pilot and validation stages of the study. Two NEPs in Queensland were used: Fortitude Valley and Cairns. These latter two sites were selected in response to a large policy change that occurred state-wide (Queensland Government, 2016). Given Fortitude Valley has a large amount of foot-traffic in the area, it enabled the technology to be stress tested. Cairns was used in the validation stage. It was believed that this area would have less foot traffic due to the cities lower population (Australian Bureau of Statistics, 2018), therefore enabling manual counts to be undertaken. Fig. 1 shows a representation of the sites used in the validation stage, the radius examined by the smartphone sensor, and the dotted line representing the path of the infrared sensor.

People counting technologies

Laptop WiFi traffic monitoring programs

The first method piloted to count the number of people in an area used mobile phone wireless signals through a WiFi traffic monitoring program, specifically the Tshark function within Wireshark (Wireshark, 2015). The program could be downloaded onto a laptop or other small device (e.g. a tablet) and placed in shopfronts in key areas within NEPs.

The program involves a network protocol analyser scanning a

network, browsing and capturing any 'traffic' or devices accessing the network, while a companion program is used to filter and export traffic captures. Devices with WiFi activated constantly send out a signal, or probe request, looking for a suitable access point to a network. These probe requests are recorded in a database, along with the time of the probe, the device type (mobile, laptop, tablet), and the MAC address (the unique identifier) of the device.

Although the program identifies all devices eliciting a WiFi signal, only mobile phone counts were utilised in the current study. Given most (95%) persons in public spaces have WiFi enabled on their phones (Abedi et al., 2013), it was expected that the counts of unique mobile phones using WiFi signals would provide an accurate representation of pedestrian traffic. In order to ensure no personal information could be obtained, only datasets using counts of the number of unique MAC addresses were analysed by the research team.

Smartphone sensor

Many companies have developed their own technology to count foot traffic in and around stores; the one used in this study was developed by Kepler Analytics (2016). The counts are conducted using a sensor that is plugged into a power point within a shop or venue.

While the sensor chosen for the current study has the capacity to count the number of WiFi signals within a 150 square metre radius, a 20 m radius was used, given this range ensures that only people using a single walkway/street are counted. The sensor identifies the WiFi signal requests in the same way as a WiFi traffic monitoring program, whereby it identifies MAC addresses of phones. The MAC addresses are used to remove instances where the same phone is being counted multiple times over a short period of time, providing a more accurate count of people within an area; this same method was used when analysing WiFi signals identified by the laptop WiFi traffic monitoring program.

The data collected by the counting sensor is uploaded to an online database in real time, this interface only provides access to the number of unique MAC addresses and not the addresses themselves. At the time of purchase, there was an initial installation fee for the sensor of AU$100, AU$80 for calibration of the sensor, and a monthly data access fee through an online dashboard of AU$100.

Infrared sensor

The infrared sensor is a portable person counting system that can count pedestrians in urban environments; the specific model used was the PYRO-Box (Eco Counter, 2016). The sensor uses a passive infrared pyroelectric technology and a high-precision lens to count people within the passing range of the sensor by detecting the person's body temperature. A person is counted when the sensor identifies a differentiation of body temperature from outside, or 'background' temperature. The sensor can simultaneously detect two people walking in a slightly staggered formation, by detecting daylight between the heat signatures of the people, however it is less accurate when there are crowds of people.

The sensor can have either a 15-metre range or 30-metre range (15 m each way from the box). The 15-metre option was selected, as the sensor was set up on the side of a foot path/road.

The data collected by the sensor is obtained by visiting the sensor in person, using Bluetooth and a mobile phone application to download the data, and then becomes available through an online database.

The cost of the sensor at the time of purchase was AU$4856.05. There is an optional cost for installation (AU$950), though self-installation is available. The cost of the license to run the software was AU$495 (covers 1–5 sensors).

Data validation

In January 2018, the infrared and smartphone sensors were used in the validation process. An infrared sensor was installed in the NEPs of Geelong and Cairns. In Cairns, a smartphone sensor was positioned in a
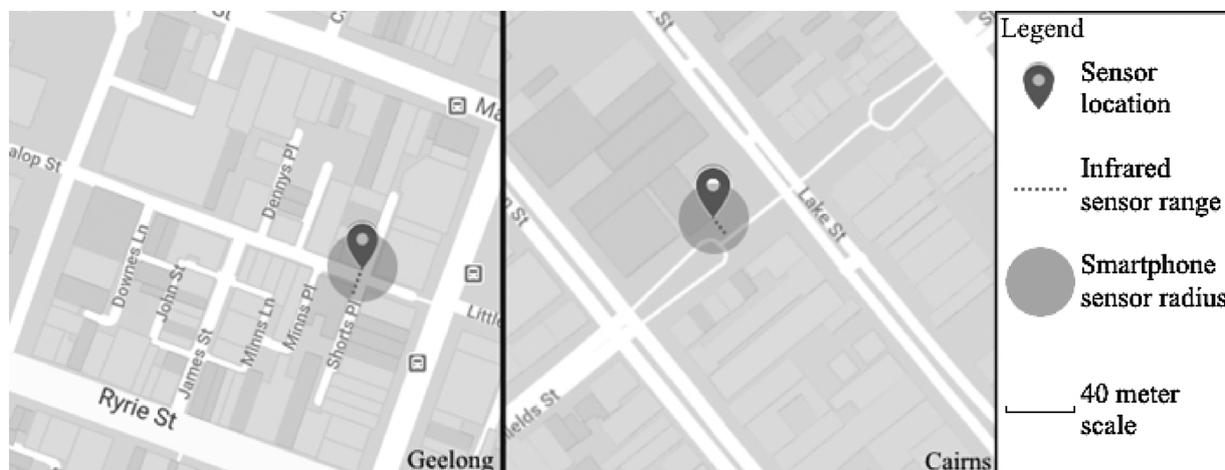
Map data: Google, DigitalGlobe ©2018

Fig. 1. Representations of validation site locations.

building along the same walkway as the infrared sensor. In Geelong a smartphone sensor (Cisco Meraki MR84; Cisco Meraki, 2018) had already been put in place, and this data was used for convenience. In addition, two observers manually counted how many people walked through each thoroughfare at each site, in four hour shifts across an eight hour night for three nights (inter-rater reliability for manual counts > .99 at both sites). This method was chosen as previous research comparing a single manual counter to video footage has demonstrated that the method has a low error rate (-0.9% to 1.4%) (Greene-Roesel et al., 2008). Manual counts took place from 6 pm to 2am on the 12th, 13th, and 14th of January 2018.

Analysis

In order to determine the accuracy of technological counting methods in the data validation stage, Pearson correlations were utilised to examine how closely each method is related to manual counts at each site. All analysis was conducted in IBM SPSS Statistics 25.0 (IBM Corp, 2017). The functionality and ease of implementation of each method will be discussed qualitatively.

Results

Stage one: pilot period

Data collected from the three pilot periods are shown in Fig. 2 below. The graphs show the average count of pedestrians per hour during high alcohol hours (8 pm Friday-6am Saturday; 8 pm Saturday-6am Sunday (Coghlan et al., 2016)). Fig. 2A shows the data collected in Geelong over a 10-week period (19/02/2016-22/04/2016) using the WiFi monitoring program. The average number of people counted varied from between approximately 15 people per hour, to 130 people per hour. The WiFi monitoring program was not able to consistently collect and record the number of people attending NEPs; the program would often cease working. Fig. 2B shows 54 weeks (12/08/2016-28/08/2017) of data collected in Fortitude Valley using the smartphone sensor. The average number of people counted per hour ranged from approximately 100 to 3500. Count data from the third method piloted, the infrared sensor, was tested in Geelong over a 6-week period (09/06/2017-14/07/2017; see Fig. 2C). The average hourly count ranged from approximately 10 people per hour to 200 people per hour.

Stage 2: data validation

Fig. 3A-C compare the manual counts to the two technology-based count methods at the Geelong sites. The infrared sensors accuracy ranged between 69% and 267% of pedestrians manually counted by observers (*SD* = 38%). The smartphone sensor ranged from 82% to 195% of manual pedestrians counts (*SD* = 30%). The two technology-based methods of counting did not vary consistently from manual counts, suggesting error was unique to each method used. When the two methods were averaged, accuracy ranged between 80% and 215% of manual counts (*SD* = 28%).

Fig. 4A-C compares the manual counts to the two technology-based count methods at the Cairns site. The infrared sensor's accuracy ranged between 43% and 69% of pedestrians manually counted by observers or smartphone sensors (*SD* = 6%). The smartphone sensor's accuracy ranged between 87% and 288% of pedestrians manually counted (*SD* = 50%). The infrared sensors variability remained relatively stable throughout the course of the night when compared to the manual counts, while the smartphone sensor was more variable over the night. When the two methods were averaged, accuracy ranged between 71% and 175% (*SD* = 26%).

Pearson correlations were run in order to examine the relationship between the different counting methods. Table 1 shows strength of the relationships between the different methods used.

Discussion

The ability to easily and effectively count the number of persons who attend NEPs is essential to provide accurate rates of alcohol-related harm, which has implications for evaluations of harm reduction measures in NEPs and policy decisions. Research has previously been forced to rely on population estimates (Miller et al., 2012, 2014; Miller, Tindall et al., 2012), which have inherent limitations. The technology-based counting methods employed in the current study were significantly related to manual counts of pedestrians over the course of a night during high-alcohol hours, in a way that could not be accounted for by an ERP. As such, they have the ability to demonstrate fluctuations in crowd trends in NEPs, and to provide insight into key times at which there are large crowds of people on the streets, without being nearly as resource intensive as requiring individuals the manually count pedestrians throughout the night. This type of information is useful for emergency services and city council resource planning, as well as the evaluation of alcohol policy changes.
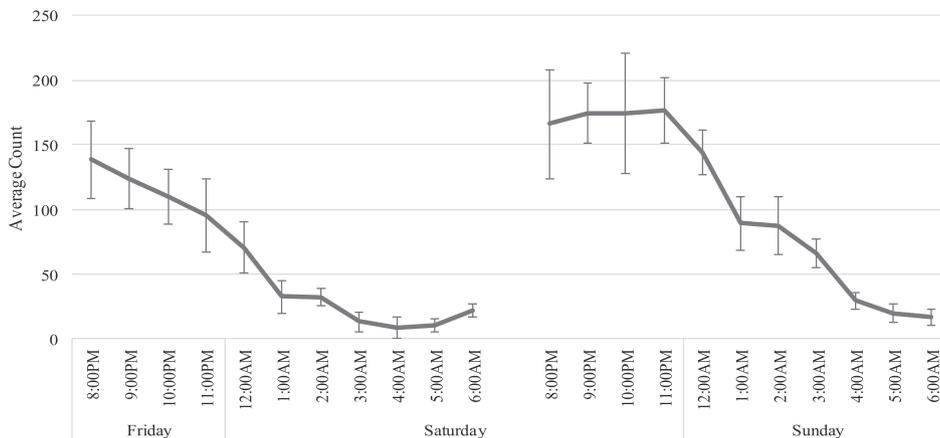
The infrared sensor was the most accurate when compared to
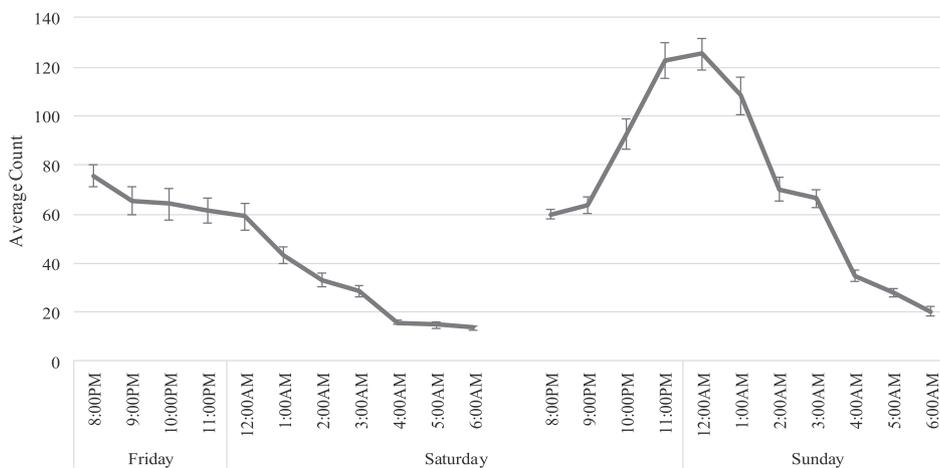
A. *WiFi monitoring program (Geelong 10 weeks)*
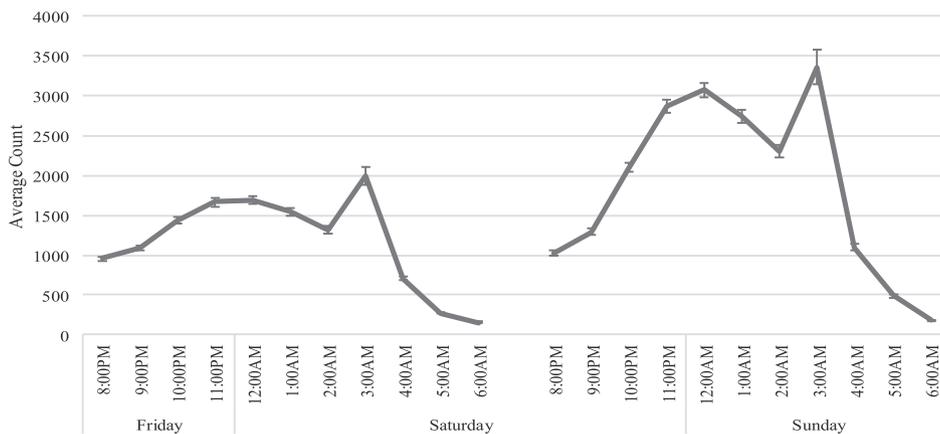
B. *Smartphone sensor (Fortitude Valley 54 weeks)*
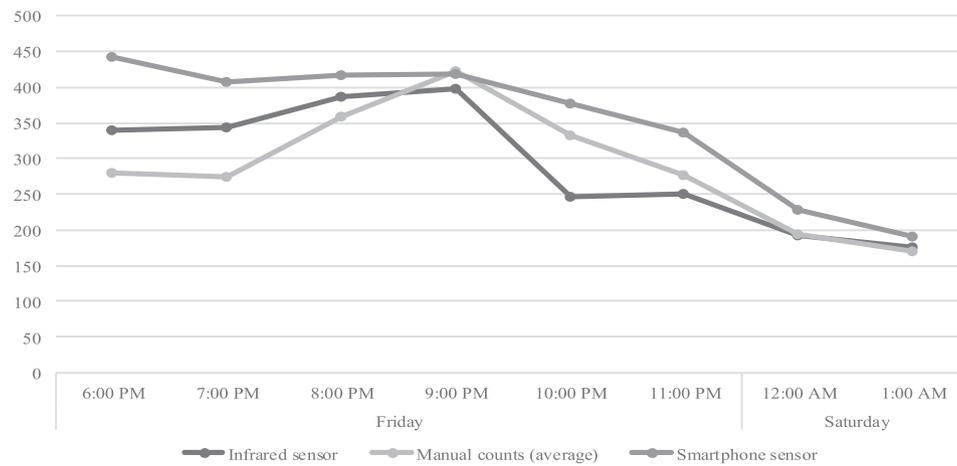

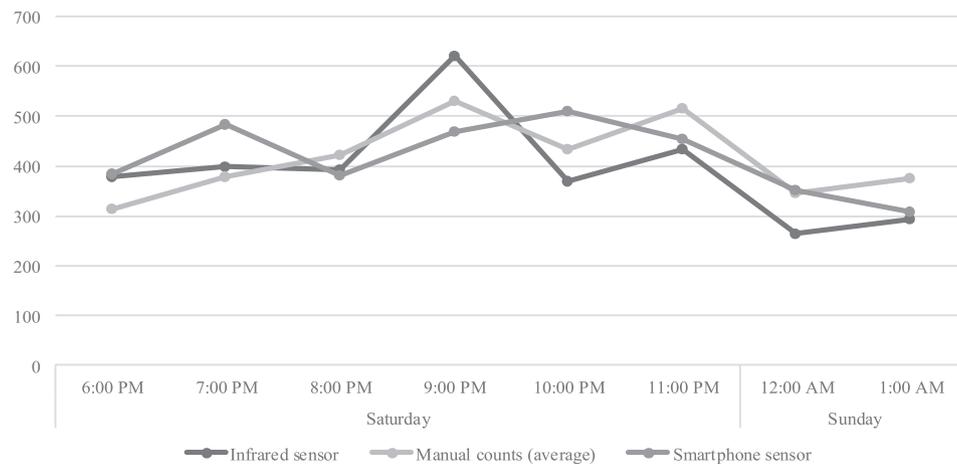**C.** *Infrared sensor (Geelong 6 weeks)*

Fig. 2. Pilot results for the WiFi monitoring program, smartphone sensor, and infrared sensor.

manual counts across both sites where it was installed. This relationship was particularly pronounced in Cairns, where the infrared sensor had the narrowest range of variation when compared to the manual counts. The main limitation of this device was the increased possibility of an anomaly creating error in the counts, as demonstrated between 11 pm and 12am on the 14th of January in Geelong (see Fig. 3C), and may explain the variance observed during peak hours during the pilot stage (see Fig. 2C). Due to the nature of this device, such errors may occur because of something blocking the device or something passing by the

sensor rapidly within a short period of time (e.g. movements in a crowd lingering in front of the sensor). The smartphone sensor was the most internally consistent of the measures tested, reporting the most reliable fluctuations in foot-traffic across different nights. The smartphone sensors had strong relationships with the manual counts across sites, however this was notably lower in Cairns. Validation of the smartphone sensor was difficult as it counted individuals in a 20 square metre radius, rather than a straight line. This may have resulted in the sensor detecting persons outside the area of interest, consistent with the trends

A. Geelong Validation - 12/01/2018
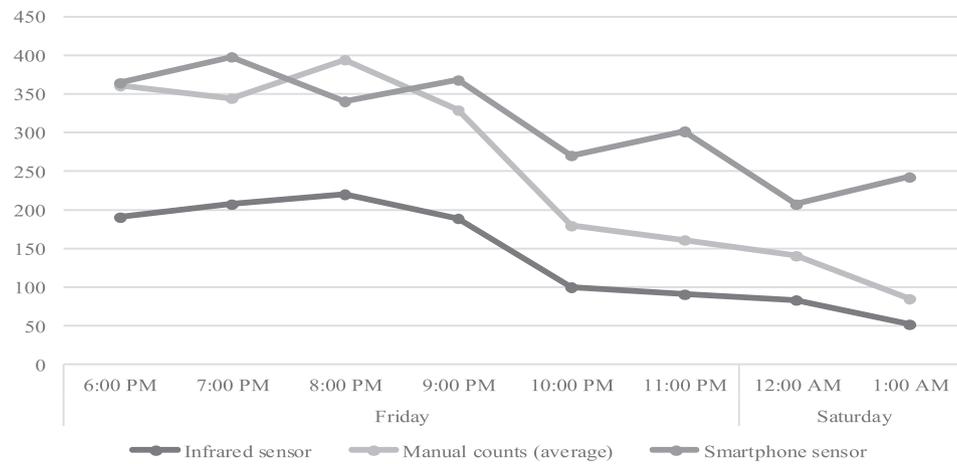

B. Geelong Validation – 13/01/2018
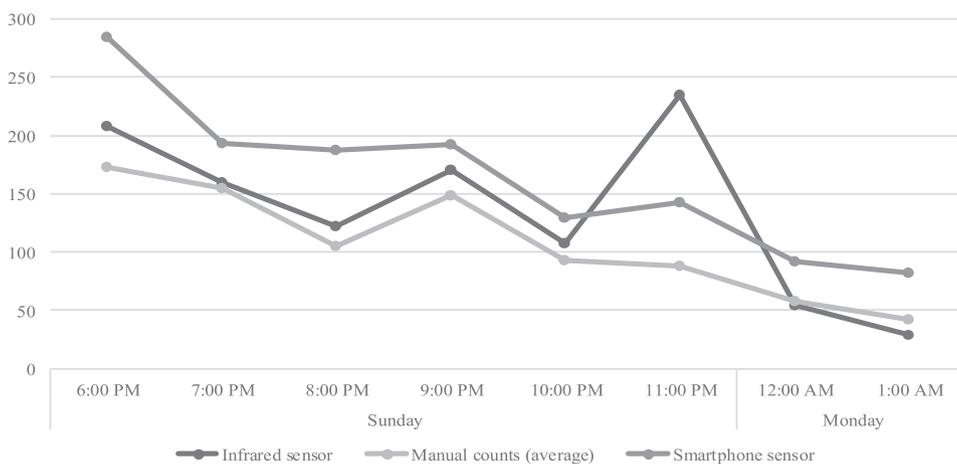
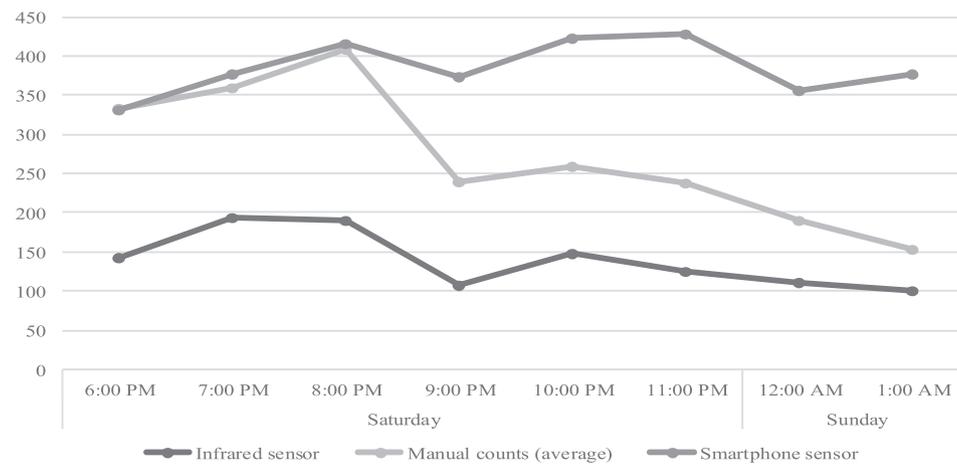C. Geelong Validation – 14/01/2018

Fig. 3. Validation of smartphone and infrared sensors - Geelong.

evident in Cairns. In Geelong, neither of the measures used in the validation stage were consistently above or below manual counts, therefore, the application of a consistent correction to technology based counts is limited. Additionally, while smartphone WiFi use in public spaces is quite high (Abedi et al., 2013), no research has determined if this is consistent in night-time spaces, where individuals may be more motivated to preserve phone battery. As such, it may be difficult to infer exact estimates of foot traffic. During the pilot stage of the project the

smartphone counting device reflected expected trends in foot traffic: the 3am peak observed in Fig. 2B reflects the trading hours restriction in Queensland (Miller et al., 2017). Smartphone sensors, and other methods that rely on identifying unique MAC addresses often raise privacy concerns, as they allow organisations to track the movements of individuals, even when security measures are enabled on these devices (Vanhoef et al., 2016). Because of this, their use in research should be subject to strict ethical guidelines. Aggregate data, as used in this study,

A. *Cairns Validation - 12/01/2018*

B. *Cairns Validation - 13/01/2018*
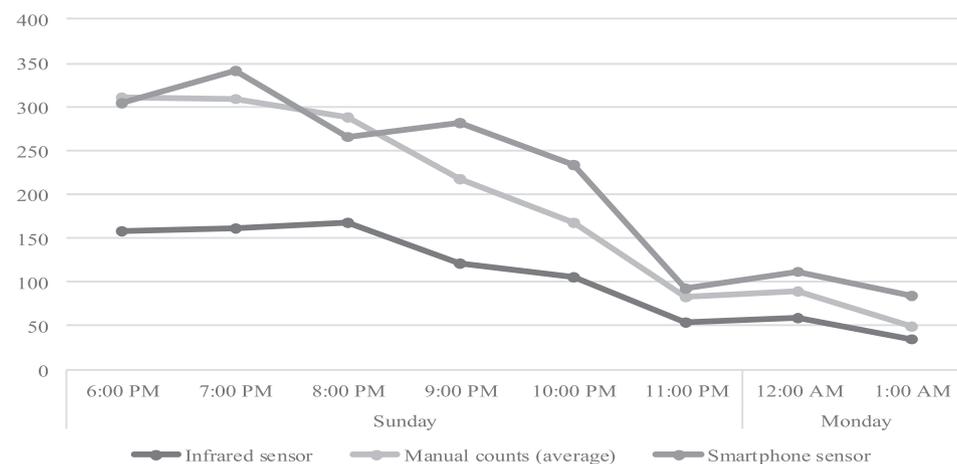
C. *Cairns Validation - 14/01/2018*

Fig. 4. Validation of smartphone and infrared sensors – Cairns.

is all that is required in order to monitor foot-traffic.

Previous work examining infrared scanners outside of NEPs found that infrared scanners systematically undercounted pedestrians across sites (Greene-Roesel et al., 2008). While this was found at the Cairns site in the current study this wasn't reflected in the results from Geelong. This study also experienced an anomalous over count on one occasion, similar to that seen in Geelong (Fig. 3C), this was also attributed to lingering in front of the sensor (Greene-Roesel et al., 2008).

The inter-rater reliability in this study was higher than that of previous manual counts in NEPs (Graham et al., 2006), this could be because the task given to manual counters was quite simplistic compared to that of previous research in the area. Greene-Roesel et al. (2008) found that manual counters given simple instructions, along walkways similar to those in the current study, had almost no error unlike studies where manual counters were required to count large groups in more complex environments. This in combination with the high level of consistency

Table 1
Correlations between different counting methods.

	Manual counts	Infrared sensor	Smartphone sensor
Geelong			
Manual counts	1	–	–
Infrared sensor	.92[*]	1	–
Smartphone sensor	.91[*]	.89[*]	1
Cairns			
Manual counts	1	–	–
Infrared sensor	.97[*]	1	–
Smartphone sensor	.74[*]	.73[*]	1

Note.

  * p < .001.

between counters indicates the results obtained were reliable estimates of pedestrian traffic.

Limitations

The foot traffic counting methods trailed do have limitations, which restrict the conclusions that can be drawn. The WiFi-traffic monitoring program was not able to consistently collect and record the number of people attending NEPs throughout the night at all sites. The program would often stop working mid-way through the night, most likely due to the program being unable to manage the sheer volume of people attending the NEP. Limiting the smartphone sensors radius by using signal strength may have been influenced by other factors that influence signal strength other than proximity to the sensor. There was also substantial variation between smartphone sensor and infrared sensor when compared to manual counts. Further validation may be required to investigate these issues in more detail. While manual counts were used to measure the validity of the other methods, they are also a proxy measure of the total number of pedestrians.

Conclusion

Accurately describing the denominator for harm in nightlife studies is crucial for ongoing research; simply relying on population estimates fails to acknowledge the distances people travel to NEPs. The findings of this study suggest that dedicated people counting devices (e.g. infrared sensor or smartphone sensor) are more reliable than Laptop WiFi Traffic Monitoring Programs at consistently detecting the number of people in NEPs. Both types of such devices that were validated showed strong, significant relationships with manual counts. The infrared sensor was the most strongly related to manual counts, and required the least in order to set up and use. For this reason it is the most highly recommended method for future research in the area. Further research is needed to identify the environmental conditions within NEPs that aid and limit the functioning of each sensor. Additionally, further research should investigate the relationships between alcohol-related harm and various characteristics of NEPs using denominators related to the actual population of the NEP, rather than ERPs.

Declaration of interests

Kerri Coomber receives funding from Australian Research Council, Foundation for Alcohol Research and Education, Lives Lived Well, Australian Rechabites Foundation, and the Queensland government.

Tanya Chikritzhs has received most of her research funding from national and international competitive grant agencies and the Commonwealth Government. She has never received alcoholic beverage industry funding. She has received economy travel class airfare from IOGT-NTO to attend meetings jointly convened by the Swedish Society of Medicine and the IOGT-NTO. Chikritzhs has also received travel funds from Systembolaget, the Swedish retail government-owned

alcohol monopoly which operates with a public health and safety mandate.

Peter Miller receives funding from Australian Research Council and Australian National Health and Medical Research Council, grants from NSW Government, National Drug Law Enforcement Research Fund, Foundation for Alcohol Research and Education, Cancer Council Victoria, Queensland government and Australian Drug Foundation, travel and related costs from Australasian Drug Strategy Conference. He has acted as a paid expert witness on behalf of a licensed venue and a security firm.

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