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Heatwaves and bus ridership, the case study of metropolitan Adelaide

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Abstract

The built environment is the majority of human habitat globally and the urban heat island effect is becoming more pronounced due to heat-absorbing materials, exacerbated by climate change. The number of roads is increasing as more people use personal vehicles, leading to induced demand and an increased urban heat island effect. Good public transport systems reduce reliance on personal vehicles and can create a lower heat island effect, but there are challenges in public adoption. A study investigated the possibility of heatwave conditions deterring bus travel, using a multiple linear regression model. The model accounted for 15% of the data collected, and heatwaves had a weak or inconclusive result. The model also revealed 10 variables with statistical significance, which can be used for predictive models on bus patronage and future studies. This study provides insights on the potential impact of heatwaves on public transport use and offers variables for future research on bus patronage.

Keywords: Public transport; Public bus; Reliability; Heatwave; Built environment; Adelaide.

1. Introduction

Global warming and the urban heat island (UHI) effect are raising metropolitan temperatures (Macintyre et al. 2018; Oke 1982; Shahmohamadi et al. 2011; Allan et al., 2022). Urban regions have the largest concentration of greenhouse gases but the lowest per capita emissions (Horowitz 2016; Longden 2019; Macintyre et al. 2018; Ghanbari et al., 2023). Cities are facing overcrowding, transport, and the effects of events like the Covid-19 pandemic as 68% of the world's population moves to urban areas by 2050. Public transport may alleviate some of these issues, although convenience and walkability affect ridership. This study uses publicly accessible data to examine the impact of heatwave conditions on public transport ridership in Adelaide, revealing the interaction of variables and mediating factors.

The research was conducted in Adelaide, South Australia, where the 30-Year Plan for Greater Adelaide (30YPGA) aimed to alleviate road infrastructure congestion to transition Adelaide towards carbon-neutrality (Department of Planning, Transport, and Infrastructure 2017). Adelaide's subtropical position makes it prone to summer heatwaves (Guan et al. 2013). The city's public transportation includes rail and light rail but is largely dominated by buses. The city's public transportation system includes buses that serve the Central Business District (CBD), ring routes, and connectors (Government of South Australia 2015; Somenahalli et al. 2013; Sun, Allan & Somenahalli 2019). The bus network includes 233 street, road, and on-demand routes, as well as a bus-only track-based O'Bahn (Allan, Nawaz & Fielke 2015; Department of Planning, Transport, and Infrastructure 2019).

The major goal of this study is to evaluate the possible impact of heatwave conditions on bus travel and discover features that may be used in bus ridership prediction models. For this goal, two main research topics have been created:

- How do heatwave conditions affect bus usage in urban areas?
- How can metropolitan Adelaide's public transport infrastructure be improved by identifying bus ridership's most important factors?

This study examines bus ridership during heatwaves and emphasizes the need of exact data in transportation studies. It highlights the importance of canopy cover in transportation conditions and urban architecture, especially in countering the effects of adverse hot weather conditions. The study provides policy-makers and urban planners with useful information to enhance public transport networks during heatwaves.

2. Literature review

Multiple factors have contributed to the Urban Heat Island (UHI) phenomenon, according to research. Climate change and heatwaves have compounded this problem. Given these constraints, urban planning methods must be modified. Public transport is being promoted as a key pathway to reduce fossil fuel use in urban areas (Chapman 2007; Comarazamy et al. 2013; Piselli et al. 2018). However, whilst public transit is sustainable and feasible under normal weather circumstances, its appeal during heatwaves and storms is compromised. These weather fluctuations may reduce public transport ridership, affecting the network's adoption rate and municipal income (Miao, Welch & Sriraj 2019).

This extensive literature study examined the many environmental elements that influence public transport utilisation. From this analytical viewpoint, knowledge gaps have been identified, prompting relevant research topics. The review discusses the contextual environment, the conditions for a predictive model, and then produces a fitted model that integrates various determining elements.

Urban populations grow, expanding urban landscapes (Neuman 2005). This expansion replaces vegetation's cooling properties with urban infrastructure's heat-absorbing materials (Oke 1982). Thus, heat is maintained and distributed into the environment, prolonging high temperatures throughout the night (Piselli et al. 2018; Shahmohamadi et al. 2011; Azhdari et al., 2018). While global temperatures rise, urban materials absorb and release heat into the environment as temperatures fall (Oke 1982). This causes a large temperature difference between urban and nature areas. Increasing thermal emissions from private vehicles amplify this phenomenon, prolonging UHI effects and urban ambient temperatures.

Globally it is estimated that 14% of greenhouse gas emissions (7.0 $GtCO_2$ in 2010) comes from transportation (IPCC 2014). Road related transport accounts for 75% of transportation emissions (The ICCT 2017). The high usage of private vehicles contributes to greenhouse gas emissions, worsening global warming. This confluence is compounded by the phenomenon of induced demand, in which the increased usage of personal vehicles leads to an increase in road infrastructure (Hymel 2019). Although the world is expected to rapidly transition to zero emissions road vehicles from 2030 onwards, the continued expansion of hard surfaced road infrastructure will exacerbate the UHI effects.

Dependability, frequency, safety perceptions, and socio-economic status affect public transportation ridership are the focus of previous studies examining ridership patterns, (Stead & Bannister 2001; Truong & Somenahalli 2015), but not on the effects of hot weather. This research examines how heatwaves affect public transit ridership in metropolitan Adelaide.

The Australian Bureau of Meteorology defines a heatwave as "three or more consecutive days of unusually high daytime and nighttime temperatures in relation to local long-term climate and recent history" (BoM 2020; Coates et al. 2014). By increasing the thermal load absorbed by materials, these heatwaves exacerbate the UHI impacts on the built environment. It is important to note that Australia has no common heatwave temperature threshold. This absence of a standardised definition is due to the subjective nature of what a local population considers thermal comfort; 30C may be hot in Tasmania but mild in Queensland.

Scholarly research shows that extreme weather conditions, including heat waves, can inconvenience individuals at public transport drop-off and pick-up zones, resulting in lower ridership (Singhal, Kamga & Yazici 2014; Tao et al. 2018; Soltani et al., 2013). Weekends are especially susceptible to weather-induced ridership changes. While weather conditions may interrupt public transport for 5% of commuters, there is no empirical data on the impact of heat wave occurrences on public transport use (Aaheim & Hauge 2005).

Mitigation measures have historically focused on shelters at transportation hubs to protect commuters from bad weather conditions. This shelter-centric strategy has reduced poor passenger patronage on bus networks (Miao, Welch & Sriraj 2019; Singhal, Kamga & Yazici 2014). It's important to note that shelter infrastructure is not the only area of investigation. The urban heat island (UHI) occurs when green areas, woods, and plants are converted into urban infrastructure, causing heat to accumulate and discharge into the urban environment. This change raises urban temperatures relative to nature (Oke 1982).

Due to high ambient temperatures, climate change, and anthropogenic heat outputs (e.g., air conditioning), numerous Australian capital cities are subtropical, making the UHI phenomena susceptible to amplification. (Anupriya 2016; Deilami & Yigitcanlar 2018; Guan et al. 2013; Sharifi, Sivam & Boland 2016). Design factors, including the creation of urban canyons that limit airflow, can exacerbate the UHI impact. A study by Deilami and Yigitcanlar (2018) demonstrated how the design of public transport networks can cause localised UHI effects, supporting the notion that design is important.

Guan et al. conducted a 2013 examination of Adelaide's UHI and found that its hotspots move over the day-night cycle. This unpredictability should be considered when developing mitigation methods and examining heatwave-related behaviour, including transportation decisions. It is important to note that although Guan et al.'s study was comprehensive, their data collecting approach, which relied on static monitors set at 4 metres and movable boom monitors installed on trucks, did not catch surface-level sidewalk temperatures. According to studies, pavement thermal temperatures may reach 67C during daytime hours, and the thermal impacts can last far into the evening owing to subsurface heat transmission (Ferguson et al. 2008; Int et al. 2013). Pavement materials can be improved to ameliorate heat retention, including the use of more permeable or reflective materials, which can reduce surface and near-surface air temperatures and improve local comfort (Ferguson et al. 2008, p. 24).

Sharifi et al. conducted a study that revealed a significant link between outdoor thermal comfort and urban heat island (UHI). Thermal comfort is psychological contentment with thermal conditions (Anupriya 2016). Physical, physiological, and psychological adaptations allowed humans to survive harsh thermal settings (Anupriya 2016). Urban streets contribute to the UHI effect, by rendering pedestrian zones thermally unpleasant for all street users, including public transit riders. Jamei & Rajagopalan conducted a computer simulation study on a Melbourne neighbourhood to investigate the effects of enhanced shade canopies on chosen roadways in the area to ameliorate the negative effects of UHI on pedestrian thermal comfort (Jamei & Rajagopalan 2018). This study determined that shade helped improve a person's thermal comfort. The creation of thermally tolerable public transit waiting places becomes possible with street trees that provide sufficient shade canopies.

Increased pavement temperatures may have a direct health impact, with surface temperatures surpassing 50C (Ferguson et al. 2008). Australia has recorded instances of heat-related contact burns, mostly in youngsters (Martin, Burrows & Wood 2015; Scanlan 2019). When temperatures exceed 41C, the risk of heat strokes increases and various pre-existing health conditions, including cardiovascular and cerebrovascular diseases, diabetes, chronic obstructive pulmonary disease, pneumonia, asthma, and influenza, are exacerbated. As heat stress-related problems become more widely recognized, this may influence urban transportation choices. Given that public transport reduces greenhouse gas emissions and mitigates the UHI effect, consideration of thermally appropriate "cooler" materials is recommended when repairing, augmenting or building new public transit facilities and their associated active transport networks. Using a "bottom-up" methodology to assess pavements independently, Roesler et al. (2015) were able to determine the contribution of footpaths to an urban area's UHI (Roesler, Sen & Technology 2015, p. 2).

A possible mitigating approach is "cool pavements." Reflective pavements increase surface albedo in materials, lowering temperatures. The subsurface or surface layers of evaporative pavements store water to cool the area (Soltani & Sharifi, 2017). Heat-harnessing pavements utilise extracted heat for various use. Both studies show thermal comfort gains for urban pedestrian users, including surface-level public transit users. However, they do not clearly examine how these materials, or their absence may affect travel behaviour patterns in locations susceptible to UHI conditions. Bus stop waiting conditions have a small impact on ridership on heat stress days. The canopy over bus stops affects ridership more than the stations themselves (Lanza & Durand 2021). On days with temperatures over 29C, ridership drops less in places with tree canopy than in those without. This indicates that individuals may not want to take public transit in hot weather conditions without a canopy or shade.

Public transport uptake is crucial to cities' greenhouse gas emission reduction and UHI mitigation initiatives, even as personal transport is electrified and powered by emissions free energy in future. The greater efficiency of public transit, even in an electrified urban transport future, will result in less heat being generated through urban transport. This review supports the concept that heat waves may affect the behaviour of individuals engaged in outdoor activities, including public transportation. Where heatwaves affect public transport use, more specialised solutions may be possible such as through street tree plantings, the use of “cool” building materials and less heat intensive road vehicles. An examination of the impact of heatwaves on public transport ridership, with an emphasis on the Adelaide bus network, is suggested given Adelaide's history of heatwaves. A predictive model was created using the specified criteria, although time and data availability restrictions prevented the collection of certain data items. This area may benefit from further investigation.

3. Methodology

This research uses only secondary data sources that were identified after a thorough systematic literature assessment. Primary data sources were not used due to time constraints associated with undertaking this research as part of a coursework postgraduate research project. This study does not include public involvement, hence it did not require human research ethics clearance. This research uses a retrospective quantitative method (Kumar 2005) to identify environmental-dependent use patterns (Bakar 2018). Due to its extensive coverage, the study focused on Adelaide's bus transport system. It utilized longitudinal ridership data from four summer four-week periods to construct trends (Bakar 2018). Anticipated events that may affect ridership, such as the Adelaide Fringe Festival, Australia Day and other public holidays, were taken into account, with the study ending three days before an event’s commencement to ensure that only routine normalised travel pattern behaviours were examined.

The longitudinal component of historical weather data must match bus ridership data for each date (Kumar 2005, pp. 110–111). Due to scheduling restrictions, data from one weather station was synchronised with the relevant week’s travel patterns. This method offered a snapshot of weather conditions on a ridership day, however adding metropolitan area weather stations would improve the granularity of the data. The research cohort for this study was made up of people from different socio-economic backgrounds. The Australian Bureau of Statistics quadrennial census provided the socio-economic data. This dataset provided a cross-sectional socio-economic profile of the population (Australian Bureau of Statistics 2022b; Phidu 2022). This dataset lacked longitudinal coverage similar to that which is available for patronage across the Adelaide bus system, hence it was repeated for each of the four study years.

Temperature and shade affect human movement (Fan, Myint & Zheng 2015; Lanza & Durand 2021). Instead of explicitly analysing bus stop canopy coverage, the study utilized DataSA's 2018 LIDAR-derived tree canopy percentages for different suburbs. Despite lacking longitudinal continuity, this data allows for a cross-sectional comparison of suburbs. Given the modest growth rate of trees, canopy coverage changes throughout the four-year study were minor, especially in Adelaide were hot dry Mediterranean summers constrain the rapidity of vegetation growth. Unfortunately, each suburb's tree canopy loss over this span is unknown. Urban infill and increasing urban densities across Adelaide’s metropolitan area has resulted in reduced tree cover due to narrower suburban streets and a loss of suburban backyards. Multiple linear regression was used to estimate bus ridership for numerous parameters (Norman 2010;

Pitsiava-Latinopoulou, Tsohos & Basbas 2001). This approach is reasonable due to the many factors that may affect bus ridership. The number of factors impacting bus ridership is significantly more than those included in this study. This research sought to identify the largest ridership influencing factors.

4. Data analysis

4.1. Data sources

Initial Concept - The initial process of data collection was to choose five main roads and obtain ridership data for all routes on those roads. Four-week periods at the height of summer for the years 2015, 2016, 2017 and 2018 were chosen. This would allow broad data gathering on both ridership behaviour as well as average summer temperatures. These four weeks were also set to end three days before the Adelaide Fringe Festival which could change the ridership count significantly and may not reflect standard bus patronage throughout other summer periods. The chosen periods for study are as follows:

2015: January 10th to February 7th

2016: January 12th to February 9th

2017: January 17th to February 14th

2018: January 16th to February 13th

Ridership Data - Data for initial ridership was obtained from the DataSA website (DataSA 2022). Plans to investigate the impact of canopy on bus ridership were initially considered but were later replaced with analysis at the suburb level due to limited data. The then Department of Infrastructure and Transport (DIT) (Government of South Australia) provided detailed passenger information for 5 routes/10 stops after an initial request for comprehensive data was deemed too extensive.

Routes were primarily chosen based on their distribution through a range of socio-economic areas. These areas were based off the 2016 Index of Relative Socioeconomic Disadvantage (IRSD) obtained via the Australian Bureau of Statistics (ABS). This is to ensure adequate representation of ridership from a diverse range of patrons (Australian Bureau of Statistics 2022b).

Bus stop selection was based on one of two criteria:

- The bus stop must have repeated ridership over the four-week periods.
- It may also have high ridership counts to highlight any variability that may occur due to high intensity heat waves.

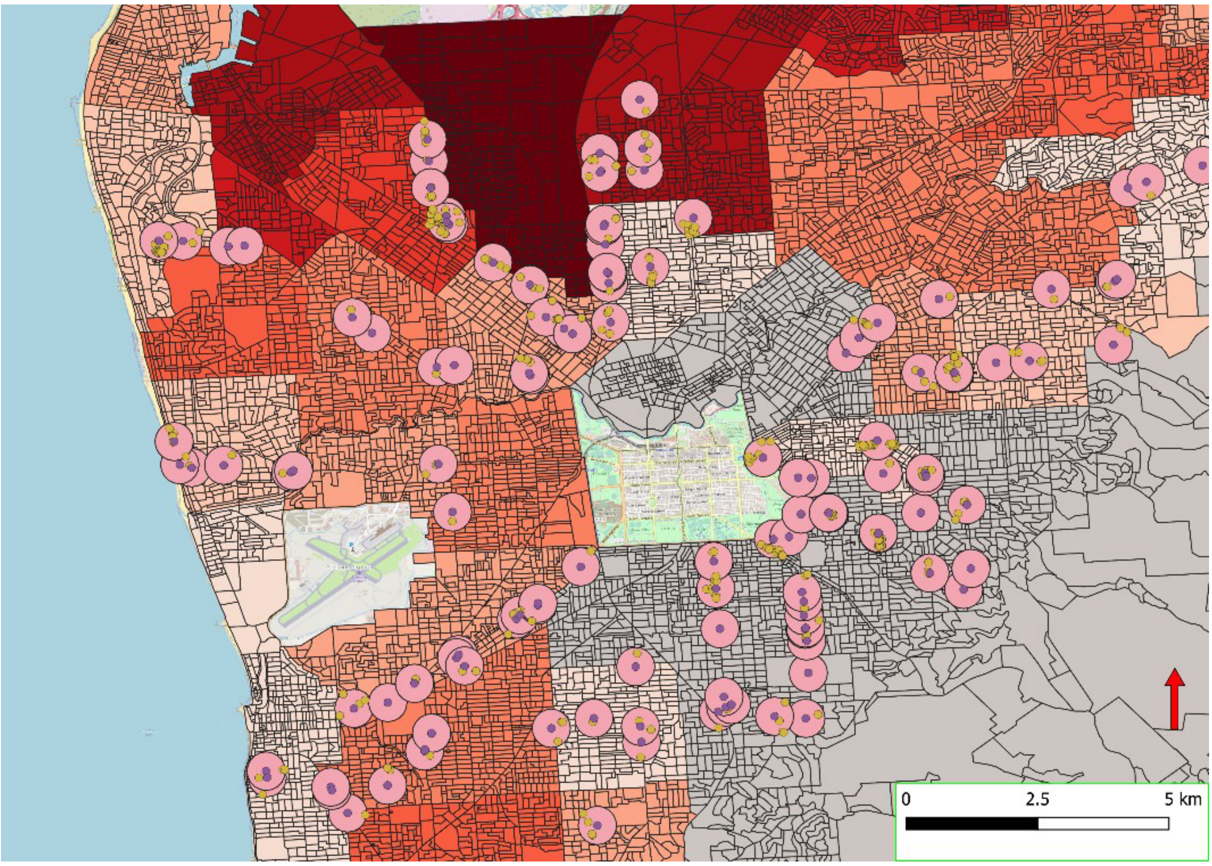
A pivot table summarized validation frequency for populous routes, cross-referenced with QGIS to map bus routes. IRSD 2016 SA-2 data from data.gov.au were matched with ABS survey area 2 boundaries and used in a GIS overlay to map routes across socio-economic areas (Australian Government 2022). Bus stops were selected based on band boarding floor count, which is the lowest number of boardings within a 10-person range of validation.

The routes and stops sent to DIT for specific ridership numbers. In response, DIT clarified that they meant 10 stops over 5 routes. However, it was determined that reducing the data set to only 10 stops over 5 routes would not provide a meaningful picture of ridership behaviour, and the time spent doing so would be significant. As a result, it was decided to use banded data and select 13 routes and 126 stops to gain higher resolution for modelling.

Canopy data - 2018 canopy data for each suburb was obtained from DataSA and paired with each bus stop location. This allowed a metric for linking heat influenced human behaviour to bus ridership.

Socioeconomic data - Socioeconomic data with a higher resolution was obtained by using ABS IRSD Survey Area 1 (SA1) data and Median Age SA1 (Figure 1) (Australian Bureau of Statistics 2022b; Phidu 2022). SA1 provides a rating for socioeconomic conditions at a higher level of granularity than the previous IRSD SA2 data. This accounts for the overall social well-being of an area as historically, people in a lower socioeconomic area are more likely to rely on public transport even in times of extreme heat (Chen & Akar 2017; Hernández-Rejón & Treviño-Hernández 2016).

Figure 1: Generated QGIS layout of bus stops, IRSDs and POI data



Frequency of transit - The frequency of the Adelaide bus network varies based on the stop. Some stops closer to the CBD have been designated as "Go Zones" which provide a maximum of a 15-minute wait time before a bus arrives during daytime hours and every 30 minutes outside of this time. Each bus stop has been designated a 1 or a 0 based on if they are a Go Zone stop. "1" denotes the inclusion of a Go Zone, 0 denotes no Go Zone. bus stop where applicable. For each bus stop, a binary value of 1 or 0 was assigned to signify if a POI was in walkable distance.

Points of interest - Points of interest (POI) were taken via the "Quick OSM" function in QGIS. This queries from a selectable list of POI types. A 400m buffer was created around each bus stop, to account for walkability of a neighbourhood and this was used to create records of walkable destinations for each.

Addition of CBD and coast data - Both the CBD and coastlines are popular destinations and have their own higher representation of transit users (Somenahalli et al. 2013). This is accounted for by the addition of calculating the distance from both the CBD and coastal Glenelg from each individual bus stop.

Weather data - Air temperature records from Adelaide airport for each day were marked against validation dates. This allows a comparison of ridership between days of normal temperatures and days that experience heatwave conditions.

Historic heatwave readings were obtained from the climate summaries archive from the BOM website (Bureau of Meteorology 2022). This information was for the same date periods as the ridership data. Based on the BOM definition of a heatwave, periods where above average maximum temperatures corresponded with above average minimum temperatures for more than three days were selected. These periods were then recorded and marked against each bus validation entry with a binary value of 1 for heatwave and 0 for non-heatwave. Temperatures for the day were also recorded and matched to bus validation.

Omissions - Three variables that proved extremely difficult to obtain were pavement materials, bus stop construction and localised surface temperatures surrounding bus shelters. Due to the limited time available for the study, individual analysis of every bus stop would have been prohibitive.

4.2. Dataset compilation and analysis

Temperature, heatwave, route, route direction and ridership validations were recorded matched to each chosen bus stop for each date.

Bus stops were matched via an intersection analysis in QGIS to determine which SA1 boundary they belonged to. SA1 boundary information allowed the mapping of IRSD, canopy cover, POI, education and occupation and Median Age of the area to each bus stop. Go zone information was obtained by querying the Adelaide metro bus route information website and marked to each bus stop (Government of South Australia 2022).

A "distance from hub" script was run on the GIS overlay to determine each bus stop distance from both the beach and CBD and this distance was then matched to each bus stop.

Due to the non-linearity of POI distances from the CBD and Beach, with significantly higher numbers for some data points, the logarithmic calculations have been used (Aaheim & Hauge

2005; Povey, Boreham & Tomaszewski 2016). The same technique was also used for canopy distribution of each suburb.

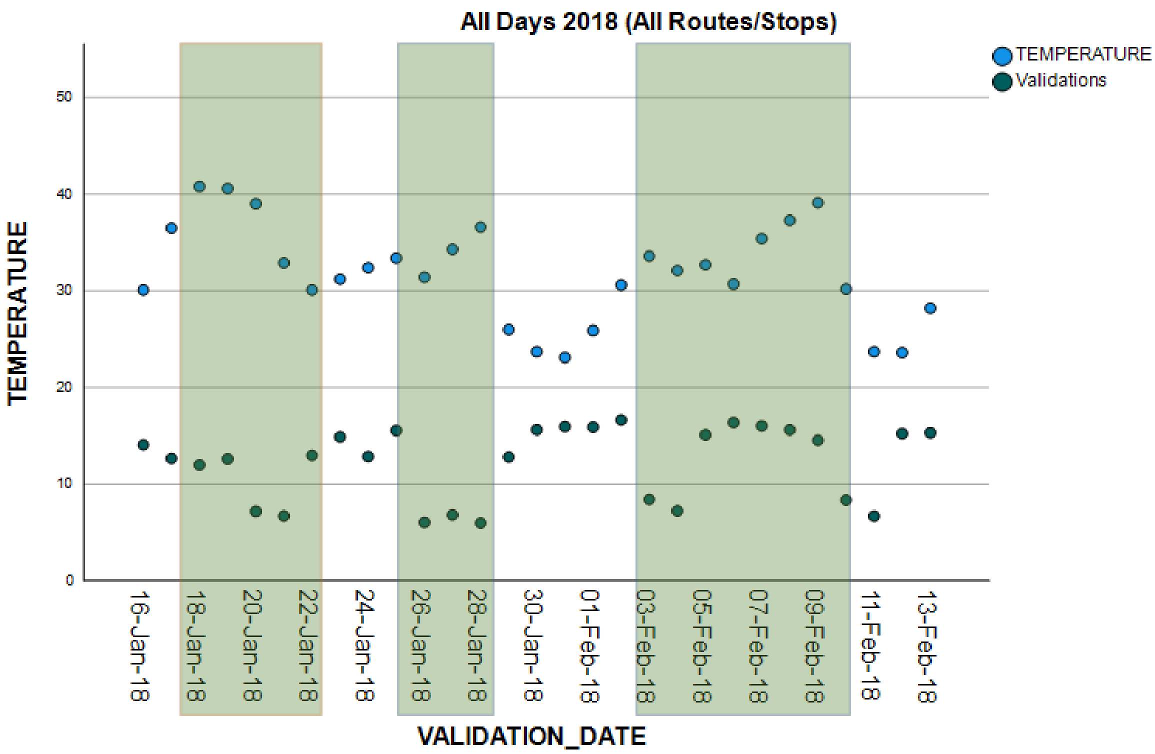
The final dataset contains a total of 13 primary variables and 25795 individual data points which are available on request.

The software used for analysing the data were: QGIS, Microsoft Excel, IBM SPSS

4.3. Initial analysis of individual routes

Ridership for routes were assembled and then matched to temperature, this was used to create an initial picture of ridership patterns. A simple scatter plot diagram was generated to inspect visually how ridership may behave under these conditions (Figure 2). Overall, there did appear to be a relationship between bus ridership and prolonged heatwave conditions. The longer heatwave conditions remained; the less bus ridership occurred.

Figure 2: Sample scatter plot of ridership versus temperature, denoting heat waves (shaded columns)



4.4. Modelling of validations

A multiple regression model was chosen as the main analysis to explore the relationship between chosen variables (Table 1) and bus patronage (Norman 2010). An R squared value of 0.2 was considered sufficient for predicting human behaviour. Variables with p-values (Sig) less than 0.05 indicate statistical significance in relation to bus patronage.

Table 1: Chosen variables for the regression model

Variable	Definition	Min	Max	Ave	Std Error
Ridership	The dependent variable used to compare all other influencing variables against.	1	210	8.787	17.0529
Route_Direction	Direction the bus was travelling primarily toward the CBD or away.	0	1	0.578	0.493879
Median_Age	Age of the population for the ABS SA1 area.	0	72	39.107	11.62441
POI	If a bus stop may have a local attraction for commuters.	0	1	0.562	0.496101
Log Canopy	Log representation of how much tree coverage is within a suburb.	2.198335	3.88732	2.896	0.388895
Temperature	Recordings of temperature for each day.	19.8	41.7	28.961	5.162757
Heatwave	Recording if the day was a heatwave.	0	1	0.224	0.416851
IRSD_SA1	The Index for relative socioeconomic disadvantage for a stop.	1	10	5.776	2.596275
GoZone_Stop	Stop is an express stop.	0	1	0.114	0.318211
Log CBD Distance	The logarithmic representation of the distance from the CBD for each bus stop.	7.544189	9.401231	8.721	0.381537
Log Beach Distance	Log of the distance to the coastal area for each bus stop.	6.834436	10.01097	9.090	0.587117
Log BeachxAge	Used to represent age groups going to or from the Beach.	0	593.94	355.976	108.0514
Log CBDxAge	Used to represent age groups going to or from the CBD.	0	650.52	340.857	104.7663

5. Results

5.1. Heatwave Model

The model summary indicates that the model can account for 15% of the data, as shown by the R-squared value of 0.150. The adjusted R-squared value is 0.149 and the standard error estimate is 15.727. ANOVA results reveal an F value of 412.933, with a significant value of .000b, indicating that the model is good and the null hypothesis is rejected.

5.1. Coefficients

The variables table shows that ten out of the eleven variables are statistically significant. The area of concern, heatwaves, shows that there is only a weak correlation between itself and validations with a significance of .067 (Table 2).

Table 2: Coefficient outputs

Variables	Coefficient	Beta	t-value	p-value
Constant	16.277		-12.113	<.001
Route Direction	.202	.154	26.349	<.001
Median Age	.408	2.478	8.908	<.001
POI	.208	.100	16.596	<.001
Log Canopy	.374	.027	3.140	.002
IRSD_SA1	.054	-.027	-3.281	.001
Go Zone Stop	.316	.084	14.264	<.001
Heatwave	.235	-.011	-1.831	.067
Log CBD	1.124	.608	24.159	<.001
Log Beach	.892	-.150	-4.892	<.001
Log CBDxAge	.030	-3.574	-19.678	<.001
Log BeachxAge	.021	.920	7.026	<.001

The standardised coefficient Beta shows that for standard deviation of heatwave results reduced ridership of -.011.

Route direction shows a very strong correlation between Route direction and ridership, for every one standard deviation of route direction, ridership increases by 0.154.

Median Age shows very strong positive correlation between Age and ridership, for every standard deviation of age increase, ridership increases by 2.478.

POI shows very strong positive correlation between bus stops that have POIs, for every standard deviation instance of POI, the ridership changes by 0.100.

Log Canopy Cover shows strong correlation between the abundance of surrounding canopy in a suburb. For every standard deviation in canopy cover, ridership increases changes by 0.027.

IRSD_SA1 shows very strong negative correlation between socioeconomic conditions and ridership. For each standard deviation in socio-economic conditions, there is an inverse change in ridership by -0.027. IRSD is rated from 1-10 with 1 being significant disadvantage and 10 being low disadvantage.

Go Zone Stop show very strong correlation, with every change in standard deviation in express bus stop, ridership increases by 0.084

Log of CBD Distance shows a very strong correlation between with every standard deviation of distance from the CBD, the ridership changes by 0.608.

Log of Beach Distance shows a very strong negative correlation, with bus ridership inversely changes by -.150 for each standard deviation in distance from the beach.

Log CBDxAGE shows very strong negative correlation, with a -3.574 change in ridership for each standard deviation the further from the CBD the service is and how old a rider is.

Log BeachxAge shows very strong correlation, with a 0.920 change in ridership the further from the beach and how old the rider might be.

5.2. Comparison to model with heatwave variable removed

Upon removal of the heatwave variable, there is very little change with the standard error of the estimate changing by 0.001. R Square remained at .150 and Adjusted R square remained at .149.

For ANOVA The F value changes positively to 453.850 and the null hypothesis was still rejected with a Sig of .000b.

5.3. Coefficients

There is little change in the coefficients, some standard deviations to present a mild change (Table 3).

Median age standardised coefficient beta changes positively by 0.002.

Log CBDxAGE standardised coefficient beta changes negatively by 0.001.

Table 3: Final coefficient outputs

Variables	Coefficient	Beta	t-value	p-value
Constant	16.286		-11.792	<.001
Route Direction	.202	.154	26.344	<.001
Median Age	.408	2.480	8.913	<.001
POI	.208	.100	16.599	<.001
Log_Canopy	.374	.027	3.151	.002
IRSD_SA1	.054	-.027	-3.278	.001
Go Zone Stop	.316	.084	14.259	<.001
Log_CBD	1.125	.608	24.165	<.001
Log_Beach	.892	-.150	-4.887	<.001
Log CBDxAge	.030	-3.575	-19.682	<.001
Log BeachxAge	.021	.920	7.022	<.001

6. Discussion

Mapped ridership and temperature initially showed a correlation between heatwaves and ridership, but refinement revealed these associations to be insignificant. The multiple regression model suggests minimal impact of heatwaves on bus ridership due to the need for additional variables reflecting human behaviour. Factors such as socio-economic conditions, distance, frequency, canopy cover, and age play a role in determining bus ridership and align with prior research (Jackisch et al. 2015; Knowles 2006; Lanza & Durand 2021; Truong & Somenahalli 2015). The model may be useful in developing a predictive model for all ridership in a city with more appropriate data to include pavement and building materials around public bus transit infrastructure.

The data used has limitations, mainly due to low resolution and incomplete records of ridership. More accurate data is needed, but obtaining it is difficult, as demonstrated in the methodology. An arrival recording is missing, which could improve the overall accuracy of the ridership picture. Mobile phone or GPS data could be an alternative option for studying pedestrian movement, but anonymizing data would require rigorous governance and ethics (Higgins et al. 2014; Teixeira, Almeida & Viana 2021).

Socio-economic data is represented by two variables: IRSD and median age. Additional indices that could be incorporated are IRSAD, Index of Economic Resources, and Index of education and occupation (Australian Bureau of Statistics 2022a). This may provide more detail as it is recommended for distributions between people with advantage and disadvantage, which would be beneficial to future models since the public bus system services both. The model's R squared value is lower than required, but the instance of ridership in relation to socioeconomic status aligns with current theory (Richmond 1996, p. 24). This creates challenges in directing adequate bus services to those most in need and in ensuring continued usage by existing bus transit patrons that do so by personal preference even where alternative modes exist. Addressing these challenges may require a cultural shift and more effective public transport systems.

The increasing data periods to encompass all days of summer to capture more heatwave data may increase accuracy, as the 2015 sample period did not have any heatwave instances in that period. Additionally, with the availability of sufficient data, it should be possible to map an entire year or more of bus ridership when using this model for predicting bus patronage. Obtaining representative information on bus stop quality could improve the accuracy of bus ridership estimates (Lanza & Durand 2021). Previous studies suggest that bus stop quality and canopy coverage influence ridership, but resource limitations precluded examination in this study. Nonetheless, shelters with full roofing and side structures are believed to be significant for maintaining ridership by protecting individuals from solar radiation and other weather elements (Lanza & Durand 2021). Future studies should include bus stop configuration as a metric in their models. While canopy data was incorporated into the model, this was at a suburb level and did not expressly consider the canopy coverage leading to a bus stop or surrounding the bus stop in general. By adding a rating system surrounding the bus stop area, this may allow for more accuracy in the model.

The study used air temperature data from only one weather station. To account for microclimate differences across the large study area, using data from multiple weather stations is recommended. This would better capture areas with higher instances of heatwaves, which may impact ridership behaviour. Future investigations should involve multiple weather stations distributed throughout the study area. Precipitation was not mapped, although it is noted that this can also be a deterrent to public transport usage (Miao, Welch & Sriraj 2019). While the summer periods in Adelaide often have minimal precipitation, rain can occasionally during the study period. If this model were the base of a year longitudinal study, precipitation should be a considered variable. Wind and cold could be additional variables to consider including.

POI data was only considered based on proximity to bus stops, without considering the number or type of POIs. A POI index including type and count may be useful in mapping patron behaviour. POI information was mapped one-to-one, so a bus stop only registers a POI if it is the closest one, which can be problematic if there are two bus stops for opposite directions.

School terms, weekends, and public holidays were included in the analysis as part of regular bus ridership. However, the possibility that school returning could have inflated bus ridership during heatwaves was acknowledged. Additionally, weekends and public holidays may have resulted in reduced ridership. To account for these factors, a variable representing changes in the school and public holidays calendar could be added to the analysis. Long travel times and frequent stopping can discourage people from using bus services due to congestion issues, which may affect personal vehicles as well. Accounting for travel time, rather than just distance from primary destinations like the CBD, could provide better insights into bus ridership, as time is often a more important factor for travellers than distance (Knowles 2006).

All Adelaide buses are air-conditioned and as such a bus ride may be seen as a welcome reprieve to the intense heat of the day. While human behaviour is altered due to heat intensity, this may reflect the route taken to the bus stop rather than catching the bus itself (Sharifi, Sivam & Boland 2016). Including qualitative information in models can enhance their predictive power and provide a more comprehensive understanding of ridership behaviour (Lu et al. 2013; Teixeira, Almeida & Viana 2021). However, using only quantitative data limits the ability to determine causation. Queries related to activity levels, active transport participation and travel frequency could improve the model's predictive qualities. Additional research focused on causal links would increase the model's reliability, but would require a more extensive study, such as on the scale of a PhD thesis project, examining additional issues through field surveys (particularly in relation to UHI effects) and changes over time with a longitudinal study. Predictive modelling involving the movement of people during different types of weather should also be investigated. A comprehensive and reliable model with the aforementioned attributes, would result in improved policy-making and transport planning that is better placed to diminish UHI effects on public transport patronage.

7. Conclusion

The aim of this study was to predict bus ridership during heatwaves using publicly available data, but the R squared value limitations resulted in the findings being inconclusive. The elimination of insignificant variables suggests heatwaves may not significantly affect bus ridership; however, the model can only explain 15% of the data. With more data and variables, the model could become a reliable tool for predicting ridership, regardless of the influence of heatwaves, but further research is needed to increase its accuracy. The study identified reliable variables for application in a multi-variant regression model thereby adding new knowledge to this field.

The study created a ridership model using freely available data and open-source software, revealing the need for efficient data retrieval tools. Gathering fine-grained ridership data is challenging, and tracking alighting passengers may require improvements in governance.

Although time-consuming, accumulating appropriate public transport data could yield a more reliable ridership model.

7.1. Policy implications

The study suggests that public transportation authorities should consider the thermal comfort of public transit infrastructure to ensure that public transit patronage levels are maintained or improved. Factors that contribute to an increased UHI, which may discourage public transit patronage, should be addressed through the choice of “cooler” materials for building surfaces, pedestrian footpaths and roadways. A model that can predict public transit ridership changes in response to public transit infrastructure improvements aimed at creating “cooler” urban environments would be very useful to the planning of public transit routes, services and infrastructure. To account for micro-climate characteristics, public transport agencies should collect air temperature records from multiple weather stations. Adding a rating system around the bus stop area, such as canopy covering, could increase the model's utility as a planning tool, particularly in optimizing attracting potential transit riders in the pedestrian catchments (pedsheds) around bus stops.

7.2. Study limitations and directions for further research

The study has limitations in terms of data resolution and scope. The then Department of Infrastructure and Transport's banded data may not provide accurate estimations of passenger behaviour. The ridership data only accounted for boarding passengers, resulting in reduced accuracy of the complete pattern of ridership from the beginning to the end of a trip. Future research could integrate other indices such as weather-related variables (i.e., wind, cold and rain), income level, employment, car ownership, and property ownership. The study could benefit from more specific information on bus stop conditions and canopy coverage, which have been shown to impact ridership. Additionally, the research only used air temperature readings from one weather station, which could be improved by using records from multiple weather stations to account for microclimate variations in each location. In addition, given the limitations of data availability, as well as the limited time and budget for this study, future research should be conducted using cause and effect models, taking into account multiple dimensions of bus ridership, and determining the weighting of heatwaves in relation to other contributing factors.

Future research could consider adding data representative of human behaviour, such as mobile phone or GPS data, to improve accuracy in investigating passenger mobility. Collecting representative data on bus stop quality would provide a more realistic picture of bus ridership. Additionally, studying the microclimate of each region would require using air temperature readings from multiple meteorological stations or taking temperature readings in the field or deriving this from satellite heat maps.

References

Aaheim, HA & Hauge, KE 2005, ‘Impacts of climate change on travel habits: A national assessment based on individual choices.’, CICERO Report, vol. 07, pp. 1–35.

Adelaide Metro (2022), viewed 20 November 2022, <https://www.adelaidemetro.com.au/>.

Adelaide Metrocard Validations (2022) - Dataset - data.sa.gov.au, viewed 22 November 2022, <https://data.sa.gov.au/data/dataset/adelaide-metrocard-validations>.

Allan, A, Nawaz, M & Fielke, M 2015, 'Transforming Adelaide into a city of networked TODs using buses: case study of the Adelaide OBahn', Australasian Transport Research Forum (ATRF), 37th, 2015, Sydney, New South Wales, Australia, pp. 1–16.

Anupriya, S 2016, 'Exploratory Study on the Relation between Urban Landscapes and Urban Corridors for Outdoor Thermal Comfort', Procedia Technology, vol. 24, pp. 1801–1807.

Australian Bureau of Statistics 2022a, .Stat Data Explorer (BETA) • SEIFA 2016 by State Suburb Code, viewed 11 June 2022, <https://explore.data.abs.gov.au/?tm=IRDS&pg=0>.

Australian Bureau of Statistics, 2022b, 2033.0.55.001 - Census of Population and Housing: Socio-Economic Indexes for Areas (SEIFA), Australia, 2016, viewed 14 June 2022, <https://www.abs.gov.au/ausstats/abs@.nsf/Lookup/by Subject/2033.0.55.001~2016~Main Features~IRSD~19>.

Australian Government 2022, ABS - Socio-Economic Indexes for Areas (SEIFA) - The Index of Relative Socio-economic Disadvantage (SA2) 2016 | Datasets | data.gov.au - beta, viewed 20 November 2022, <https://data.gov.au/dataset/ds-aurin-c6baaa6a-4886-4ac0-b4da-cefd716352db/details?q=IRSD>.

Azhdari, A., Soltani, A., & Alidadi, M. (2018). Urban morphology and landscape structure effect on land surface temperature: Evidence from Shiraz, a semi-arid city. Sustainable cities and society, 41, 853-864.

Bakar, AHA 2018, A Complete Guide to Academic Research In Built Environment and Engineering (Penerbit USM), Penerbit USM.

Böcker, L, Dijst, M & Prillwitz, J 2013, 'Impact of Everyday Weather on Individual Daily Travel Behaviours in Perspective: A Literature Review', Transport Reviews, vol. 33, no. 1, pp. 71–91.

BoM 2020, Understanding Heatwaves, Heatwave Knowledge centre- Bureau of Meteorology, viewed 6 November 2022, <http://www.bom.gov.au/australia/heatwave/knowledge-centre/understanding.shtml>.

Bureau of Meteorology 2022, Climate summaries archive, viewed 18 November 2022, <http://www.bom.gov.au/climate/current/statement_archives.shtml?region=sa&period=month>.

Chapman, L 2007, 'Transport and climate change : a review', Journal of Transport Geography, vol. 15, pp. 354–367.

Chen, N & Akar, G 2017, 'How do socio-demographics and built environment affect individual accessibility based on activity space? Evidence from greater Cleveland, Ohio', Journal of Transport and Land Use, vol. 10, no. 1, pp. 477–503.

Coates, L, Haynes, K, O'Brien, J, McAneney, J & De Oliveira, FD 2014, 'Exploring 167 years of vulnerability: An examination of extreme heat events in Australia 1844-2010', Environmental Science and Policy, vol. 42, pp. 33–44.

Comarazamy, DE, GonzáLez, JE, Luvall, JC, Rickman, DL & Bornstein, RD 2013, 'Climate impacts of land-cover and land-use changes in tropical islands under conditions of global climate change', Journal of Climate, vol. 26, no. 5, pp. 1535–1550.

DataSA 2018, Metropolitan Adelaide Canopy and Permeability Statistics 2018-19 - Dataset - data.sa.gov.au, viewed 22 November 2022, <https://data.sa.gov.au/data/dataset/metropolitan-adelaide-canopy-and-permeability-statistics-2018-19>.

Deilami, K & Yigitcanlar, T 2018, 'Investigating the urban heat island effect of transit oriented development in Brisbane', Journal of Transport Geography, vol. 66, no. November 2017, pp. 116–124.

Department of Planning Transport and Infrastructure 2017, The 30-Year Plan for Greater Adelaide.

Fan, C, Myint, SW & Zheng, B 2015, 'Measuring the spatial arrangement of urban vegetation and its impacts on seasonal surface temperatures', Progress in Physical Geography, vol. 39, no. 2, pp. 199–219.

Ferguson, B, Fisher, K, Golden, J, Hair, L, Haselbach, L, Hitchcock, D, … Waye, D 2008, 'Reducing urban heat islands: compendium of strategies-cool pavements', Environmental Protection Agency, vol. 12, p. 39p.

Gkiotsalitis, K & Cats, O 2021, 'Public transport planning adaption under the COVID-19 pandemic crisis: literature review of research needs and directions', Transport Reviews, vol. 41, no. 3, pp. 374–392.

Government of South Australia 2015, Integrated Transport and Land Use Plan, no. October.

Guan, H, Bennett, J, Ewenz, C, Benger, S, Zhu, S, Clay, R & Soebarto, V 2013, 'Characterisation, interpretation and implications of the Adelaide urban Heat Island', Journal of the American Planning Association.

Hatvani-Kovacs, G, Bush, J, Sharifi, E & Boland, J 2018, 'Policy recommendations to increase urban heat stress resilience', Urban Climate, vol. 25, pp. 51–63.

Hernández-Rejón, E & Treviño-Hernández, R 2016, 'Gender Perspective in Urban Research', Vivat Academia, vol. 19, no. 134, pp. 48–56.

Herranz-Pascual, K 2014, 'Urban thermal comfort: proposed questionnaire to evaluate its social perception (Q-CTUp) / Confort térmico urbano: propuesta de un cuestionario para medir su percepción social (Q-CTUp)', Psyecology, vol. 5, no. 2–3, pp. 317–349.

Higgins, E, Taylor, M, Lisboa, P & Arshad, F 2014, 'Developing a data sharing framework: A case study', Transforming Government: People, Process and Policy, vol. 8, no. 1, pp. 151–164.

Horowitz, CA 2016, 'Paris Agreement', International Legal Materials, vol. 55, no. 4, pp. 740–755.

Hymel, K 2019, 'If you build it, they will drive: Measuring induced demand for vehicle travel in urban areas', Transport Policy, vol. 76, no. August 2018, pp. 57–66.

IPCC (2014) Summary for Policymakers. In: Climate Change 2014: Mitigation of Climate Change. Contribution of Working Group III to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change [Edenhofer, O., R. Pichs-Madruga, Y. Sokona, E. Farahani, S. Kadner, K. Seyboth, A. Adler, I. Baum, S. Brunner, P. Eickemeier, B. Kriemann, J. Savolainen, S. Schlömer, C. von Stechow, T. Zwickel and J.C. Minx (eds.)]. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Int, I, Res, JP, Maria, V Di, Rahman, M, Collins, P, Dondi, G & Sangiorgi, C 2013, 'Urban Heat Island Effect : thermal response from different types of exposed paved surfaces', vol. 6, no. 4, pp. 414–422.

Jackisch, J, Zamaro, G, Green, G & Huber, M 2015, 'Is a healthy city also an age-friendly city?', Health Promotion International, vol. 30, pp. i108–i117.

Jamei, E & Rajagopalan, P 2018, 'Effect of street design on pedestrian thermal comfort', Architectural Science Review, vol. 0, no. 0, pp. 1–20.

Knowles, RD 2006, 'Transport shaping space: differential collapse in time-space', Journal of Transport Geography, vol. 14, no. 6, pp. 407–425.

Kumar, R 2005, Research Methodology: a step-by-step guide for beginners, 3rd edn, vol. 50, SAGE Publications Ltd, no. 2.

Lanza, K & Durand, CP 2021, 'Heat-moderating effects of bus stop shelters and tree shade on public transport ridership', International Journal of Environmental Research and Public Health, vol. 18, no. 2, pp. 1–15.

Longden, T 2019, 'The impact of temperature on mortality across different climate zones', Climatic Change, vol. 157, no. 2, pp. 221–242.

Lu, X, Wetter, E, Bharti, N, Tatem, AJ & Bengtsson, L 2013, 'Approaching the Limit of Predictability in Human Mobility', pp. 1–9.

Macintyre, HL, Heaviside, C, Taylor, J, Picetti, R, Symonds, P, Cai, XM & Vardoulakis, S 2018, 'Assessing urban population vulnerability and environmental risks across an urban area during heatwaves – Implications for health protection', Science of the Total Environment, vol. 610–611, pp. 678–690.

Martin, L, Burrows, SA & Wood, FM 2015, 'Heatwave and risk of heat-related burn injury to children in Western Australia', Medical Journal of Australia, vol. 203, no. 2, pp. iii–iv.

Miao, Q, Welch, EW & Sriraj, PS 2019, 'Extreme weather, public transport ridership and moderating effect of bus stop shelters', Journal of Transport Geography, vol. 74, no. November 2018, pp. 125–133.

Neuman, M 2005, ‘The compact city fallacy’, Journal of Planning Education and Research, vol. 25, no. 1, pp. 11–26.

Norman, G 2010, ‘Likert scales, levels of measurement and the “laws” of statistics’, Advances in Health Sciences Education, vol. 15, no. 5, pp. 625–632.

Oke, TR 1982, ‘The energetic basis of the urban heat island’, Quarterly Journal of the Royal Meteorological Society, vol. 108, no. 455, pp. 1–24.

Phidu 2022, Index of Relative Socio-economic Disadvantage - Phidu, viewed 10 June 2022, <https://phidu.torrens.edu.au/notes-on-the-data/demographic-social/irsd>.

Piselli, C, Castaldo, VL, Pigliautile, I, Pisello, AL & Cotana, F 2018, ‘Outdoor comfort conditions in urban areas : On citizens ’ perspective about microclimate mitigation of urban transit areas’, Sustainable Cities and Society, vol. 39, no. December 2017, pp. 16–36.

Pitsiava-Latinopoulou, M, Tsohos, G & Basbas, S 2001, ‘Trip generation rates and land use - Transport planning in urban environment’, Advances in Transport, vol. 8, pp. 297–306.

Povey, J, Boreham, P & Tomaszewski, W 2016, ‘The development of a new multi-faceted model of social wellbeing: Does income level make a difference?’, Journal of Sociology, vol. 52, no. 2, pp. 155–172.

Qaid, A, Bin Lamit, H, Ossen, DR & Raja Shahminan, RN 2016, ‘Urban heat island and thermal comfort conditions at micro-climate scale in a tropical planned city’, Energy and Buildings, vol. 133, pp. 577–595.

Qin, Y 2015, ‘A review on the development of cool pavements to mitigate urban heat island effect’, Renewable and Sustainable Energy Reviews, vol. 52, pp. 445–459.

Richmond, J 1996, ‘Designing Transport & Urban Forms for the Australia of the 21st Century’, Transport, no. April.

Roesler, J, Sen, S & Technology, I 2015, ‘Impact of pavements on the urban heat island’.

Scanlan, R 2019, Australia heatwave: Toddler suffers third degree burns walking on pavement, news.com.au, viewed 10 April 2019, <https://www.news.com.au/lifestyle/parenting/kids/toddler-suffers-awful-burns-to-feet-after-walking-on-hot-path/news-story/4e9ff68714a44cbdd72cd5683e1dccd3>.

Shahmohamadi, P, Che-Ani, AI, Etessam, I, Maulud, KNA & Tawil, NM 2011, ‘Healthy environment: The need to mitigate urban heat island effects on human health’, Procedia Engineering, vol. 20, pp. 61–70.

Sharifi, E, Sivam, A & Boland, J 2016, ‘Resilience to heat in public space: a case study of Adelaide, South Australia’, Journal of Environmental Planning and Management, vol. 59, no. 10, pp. 1833–1854.

Silva, EA, Healey, P, Harris, N & Broeck, P Van Den 2014, The Routledge Handbook of Planning Research Methods, Taylor and Francis, no. 2014.

Singhal, A, Kamga, C & Yazici, A 2014, ‘Impact of weather on urban transit ridership’, Transportation Research Part A: Policy and Practice, vol. 69, pp. 379–391.

Soltani, A., & Allan, A. (2006). Analyzing the impacts of microscale urban attributes on travel: Evidence from suburban Adelaide, Australia. Journal of urban planning and development, 132(3), 132-137.

Soltani, A., & Sharifi, E. (2017). Daily variation of urban heat island effect and its correlations to urban greenery: A case study of Adelaide. Frontiers of Architectural Research, 6(4), 529-538.

Somenahalli, S, Sleep, C, Primerano, F, Wadduwage, R & Mayer, C 2013, ‘Public Transport Usage in Adelaide’, Procedia - Social and Behavioral Sciences, vol. 104, pp. 855–864.

Stead, D & Banister, D 2001, ‘Influencing Mobility Outside Transport Policy’, Innovation: The European Journal of Social Science Research, vol. 14, no. 4, pp. 315–330.

Steemers, K & Nikolopoulou, M 2003, ‘Thermal comfort and psychological adaptation as a guide for designing urban spaces’, Energy and Buildings, vol. 35, p. pp 95-101.

Stone, B, Vargo, J, Liu, P, Hu, Y & Russell, A 2013, ‘Climate Change Adaptation Through Urban Heat Management in Atlanta, Georgia’.

Tao, S, Corcoran, J, Rowe, F & Hickman, M 2018, ‘To travel or not to travel: “Weather” is the question. Modelling the effect of local weather conditions on bus ridership’, Transportation Research Part C: Emerging Technologies, vol. 86, no. October 2017, pp. 147–167.

Teixeira, C, Almeida, JM & Viana, AC 2021, ‘On estimating the predictability of human mobility: the role of routine’, EPJ Data Sci.

The ICCT (2017) Status of policies for clean vehicles and fuels in select G20 countries. Accessed at https://www. theicct.org/sites/default/files/publications/Status-of-policy- post-TTG_ICCT-Briefing_15082017_vF.pdf

Truong, LT & Somenahalli, SVC 2015, ‘Exploring frequency of public transport use among older adults: A study in Adelaide, Australia’, Travel Behaviour and Society, vol. 2, no. 3, pp. 148–155.

United Nations 2018, ‘World Urbanization Prospects: Key Facts’, United Nations Economic & Social Affairs, pp. 1–2.

Vickerman, R 2021, ‘Will Covid-19 put the public back in public transport? A UK perspective’, Transport Policy, vol. 103, pp. 95–102.