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A new employment market segmentation for transport models: a case study in South-East Queensland, Australia

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Abstract

The conventional blue/white collar market segmentation has dominated travel demand modelling since the 1960s. Many city-region transport models have therefore struggled to keep up with systemic changes in Australian labour markets, especially the growing participation of women. Our aims were to help the Queensland Government develop a new commuter classification structure for the Brisbane Strategic Travel Demand Model using the latest South East Queensland Travel Survey data. An inductive approach is used, identifying from within the data itself what might be improved groupings of commuters for market segmentation. Using cluster analysis, commuter types are grouped by a key set of occupational, industry, and socio-demographic variables (i.e., gender, age, household size, household vehicle ownership and worker skill score). The results reveal there are distinct types of commuters that cannot be easily combined into one or two groups. We propose a market segmentation of three types of workers for SEQ. This includes revisions to what are the previous 'blue' and 'white' collar workers, and a new female-dominated type, which we call 'pink-collar' workers. All have distinct travel behavior characteristics. 'Blue collar' workers travel longer distances to work and show the highest levels of dependence on private motor vehicles; 'white collar' workers have the lowest car dependence and greatest use of public transport and travel relatively short trip distances. 'Pink-collar' workers have the shortest median commutes. This is in line with previous research on Australian households showing that women often take work closer to home to be closer to schooling and childcare.

1.Introduction

Conventional employment market segmentation in the Brisbane Strategic Travel Demand Model (BSTM) used a very coarse level of differentiation; employees were categorised either as 'white collar' or 'blue collar' workers. This conventional blue/white collar segmentation concept was widely adopted in the travel mode choice modelling area from the early development of the field in the 20th Century. However, this old blue collar/white collar duality is increasingly inappropriate, considering the significant increase in paid labour force participation and commuting made by women. By the 1990s, researchers understood a sex-related occupational differentiation in the labour market, with nearly two-thirds of women working in occupations in which they are either highly over-represented or highly under-represented (Barron and Norris, 1991). As such, travel behavior studies began to focus on gender from many perspectives, including differences in distance to work, mode of travel and automobile occupancy and the propensity to trip chain by men and women (McGuckin et al., 2005). However, this gender division has not always made it through to the market segmentation used in many Australian transport models.

Women and men who work in the same occupational category can have different commuting patterns (Rosenbloom and Burns, 1994). To our knowledge, workers are simplified into the “white collar” and “blue collar” groups in the current BSTM based solely on their occupations, with “white collar” workers being ANZSCO categories 1,2,4,5 and 6 (Managers, Professionals, Community and Personal Service workers, Clerical and Administrative Workers, Sales Workers); and “blue collar” workers categories 3, 7 and 8 (Technicians and Trades Workers, Machinery Operators and Drivers, Labourers). Can this dual market segmentation strategy sufficiently explain the current labour market in transport models today? Or should a different market segmentation be employed?

This paper reports on the methods used to develop a new and novel worker classification structure, for the future improvement of the current BSTM. As will be shown, it uses an inductive approach. Three main research questions were initially developed:

1) what is the current employment market structure in SEQ?

2) how are employment types reflected in journey-to-work travel behavior?

3) are the differences in commuter type identified sufficient to warrant them potentially being taken forward for testing of improved formulations of the BSTM?

These issues were evaluated among workers using the 2017-2020 datasets of the South East Queensland Travel Survey, the region’s main rolling household travel survey program. A series of unsupervised iterative k-medoids clustering processes were adopted to reveal groups at different numbers of clusters; travel behavior analysis for each group was conducted to provide insights into a more appropriate segmentation strategy for transport modelling.

Historically, most studies recognized the importance of socio-demographic’s (especially income) and their impact on commuting behaviour, but treated occupation as having more of a secondary influence (Cubukgil and Miller, 1982). In theory, occupational groups should have different preferences for certain residential locations and different willingness and ability to travel. As commuting behaviour is influenced by workers’ employment and residential location decisions, different occupation groups can have quite distinct commuting patterns (Cubukgil and Miller, 1982). Yet most models have not deviated from approaches used way back in the 1965 Brisbane Transportation Study, which segmented the employment market into blue/white collar workers. Given the rise of service workers and other in a more complex mix, this seems on face value inappropriate.

2. Background

2.1. Evolution of labor force

During much of the twentieth century, employment has been viewed as “standard”- full-time and permanent waged, where the male was the main income earner and female was the main domestic carer (Broomhill and Sharp, 2005). Since the latter part of twentieth century, journey-to-work patterns have transformed due to changes in the nature of employment, transportation costs, economic shifts, increasing female workforce participation rate in labour market and public policies which increasingly favour labour mobility and uncertainty etc. (Standing, 2012; Thévenon, 2013). The rise of gig economy and telecommuting workers (Spreitzer et al., 2017, p. 475), the expansion of the service industry and decline in manufacturing added more complexity. Modellers are struggling to model the resulting commuter behaviour.

The term ‘blue collar’ to identify manual labour workers first appeared at the beginning of the 20th century and increased the popularity of the term ‘white collar’ which identifies a class of administrative workers (Elser et al., 2018). Since the latter part of twentieth century, journey-to-work patterns have transformed, induced by changes happening in the nature of employment, transportation costs, economic shifts, increasing female workforce participation rates and public policies which are increasingly favouring labour mobility (Thévenon, 2013). Insights into the potential relationship between employment types and their commuting behaviours include understandings that the mode and travel time are particularly important for workers whose travel is a derived demand, and whose daily movements are constrained by spatial and temporal constraints.

In the post-World War II period, Australia’s economy was dominated by manufacturing and, increasingly, mining (Langford & Male, 2001). With high tariffs on imported goods, firms hired workers in steelworks, automobile and chemical plants, and a range of other factory industries. With low female participation, and with limited computing power, a simple white/blue collar split was a reasonable approach for modellers to employ. A series of structural changes in the 1970s and 1980s saw a shift towards a post-industrial future. Tariffs were reduced, the Commonwealth and the states sold off utilities, airlines, airports, etc., and the economy was increasingly liberalised. Australia began to import more manufactured goods than it made locally. Machines replaced many workers in the factories and then also in the mines. Knowledge work, including in sectors such as finance, banking and education, and services work, including in health, began to increase as the total number of employees in manufacturing and labouring industries fell. The forms ‘blue-collar’ and ‘white collar’ employment take today differ from those of previous eras. Workers in many Australian factories may have more advanced skills and higher education training than the early migrant workers of the past. They may work for more than one employer over a lifetime and be increasingly flexible in terms of their work arrangements. Many of the previously unionised tradesmen (electricians, plumbers, etc.) who worked for big construction firms or utilities in the 1960s are today self-employed contractors, effectively small business owners whose key assets are their labour and their skills. ‘Portfolio workers’, who trade on their knowledge may work as contractors to multiple employers, perhaps based from a co-workspace (shared by multiple micro-firms rather than one big employer) in the inner city. The ‘gig-economy’ of smart-phone apps (Uber, Deliveroo, etc.) has created a new class of worker, with minimal labour protections, referred to as ‘Insta-serfs’ (Kuhn and Maleki, 2017). To classify all these worker types using a 1960s division of ‘blue collar’ and ‘white collar’ seems inappropriate.

But again, there has been little analysis of these trends, or of what a more robust market segmentation of work might look like for mode choice modelling.

2.2. Employment market segmentation in transport models

The origins of the ‘white collar’ and ‘blue collar’ employment classifications, and the use of this classifications in travel demand modelling appears to come from the early days of four-step travel demand modelling. The Detroit Metropolitan Area Traffic Study (1955) took ratios of workers per 1,000 residents for selected industrial plants, and ratios of workers per 1,000 residents for persons working within the core area of the central business district, to specify the employment market, indicating the distinction between blue and white collars without actually using those terms. Similarly, the Chicago Area Transportation Study (1959) used the terms ‘commercial’ and ‘manufacturing’ to describe existing distinctions in the employment market. The 1965 Brisbane Transportation Study (Willbur and Associates, 1965, pp. 127-128) adopted a more detailed classification of the employment market (i.e., primary production, manufacturing, building and public services, business services and commerce, public authority and professional services, personal services and other industries). Some fifty years later, the BSTM is still using similar classifications (‘blue/white collar’ for the employment market) despite all the changes in labour force markets which have occurred during the last 60 or more years.

In Australia, according to ANZSCO (Australian and New Zealand Standard Classification of Occupations, 2013, Version1.2), there are 1,023 occupations classified into 8 major groups: managers, professionals, technicians and trade workers, community and personal service workers, clerical and administrative workers, sales workers, machinery operators and drivers, and labourers (ABS, 2013). As illustrated in Figure 1, those major groups are further categorized into ‘white/blue collar’ (see Veitch Lister Consulting (2014). A number of Australian models have moved to a different labour market segmentation, including the main Sydney model, as have models overseas. Methodologically, most of these changes have been driven by a deductive research approach, with the experts making informed guesses as to what might be better segmentations, then testing those to see if they produce more realistic results. That may be fine in practice, but not overly robust in theory.

ANZSCO1 classification	White / blue
1. Managers	White
2. Professionals	White
3. Technicians and Trades Workers	Blue
4. Community and Personal Service Workers	White
5. Clerical and Administrative Workers	White
6. Sales Workers	White
7. Machinery Operators and Drivers	Blue
8. Labourers	Blue

Figure 1. Definition of blue/white collar (using ANZSCO1). Adapted from Zenith Model Framework Papers - Version 3.0.1, Paper B – Household Segmentation Model (p. 10) by Veitch Lister Consulting, 2014

2.3. Importance of reappraisal of the blue/white collar dichotomy in transport models

The growth and transformation of labour force (e.g., rise of the information technologies, female labour participation rates) in cities over the past fifty years brought significant impact on commuting behaviour. The simple blue/white collar dichotomy in transport models clearly is inefficient to describe today's labour force market.
The dispersal of information-dominated activities in certain occupations supported 'telecommuting' - people's working-from-home and decentralized workstations, which became vital during the COVID-19 pandemic. In addition, the unifying general argument that women suffer from several constraints, limiting the work trip distance and commuting mode preference, has been widely discussed by researchers in the field, despite of the various explanations among them. Many of the previous research studies (Collins & Tisdell, 2002; Crane, 2007) observed the gender difference in commuting behaviour. Nevertheless, studies about how to incorporate the gender difference and how to reappraisal the blue/white collar dichotomy in transport model remain very scarce. As will be shown, there is a significant gap in knowledge in this area.

The dataset we adopted was collected before the pandemic, thus the popularity of telecommuting induced by COVID-19 and how this will impact future commuting behaviour in a long term is not the focus of this research.

3. Method

In this study, an inductive, unsupervised clustering process was adopted. The underlying assumption of market segmentation is that people with different characteristics place different importance on different aspects of service (see Ben-Akiva, et al., 1985; Koppelman and Bhat, 2006). In the BSTM at present, female dominated occupations such as health, education, community and personal service workers are subsumed as part of the very broad white/blue collar classification. This aggregation helps with model simplicity and run-time but does not reflect reality all that well.

The clustering process used differentiates employees via the following socio-demographic characteristics – gender, age, ANZSCO1- Australian and New Zealand Standard Classification of Occupations 1, skill score, working industry type, household size, household vehicle ownership, and household bicycle ownership in the clustering process.

ANZSCO is a skill-based classification used to classify all occupations and jobs, and group them into successively broader categories for statistical and other types of analysis based on the similarity of their attributes in the Australian and New Zealand labour markets. Using aspects of both skill level and skill specialisation, sub-major groups are grouped into eight major groups. ANZSCO1 represents the broadest level of ANZSCO with 8 major groups and ANZSCO3 represents for minor groups with a less broad application of skill specialisation. In this study, the skill specialisation for ANZSCO3 is adopted as it is more comprehensive.

Skill level, ranging from 1 to 5 (Skill level 1 is the highest and commensurate with a bachelor's 1degree or higher, while skill level 5 is the lowest and commensurate with a Certificate I or compulsory secondary education), is measured operationally by the level or amount of formal education and training, the amount of previous experience in a related occupation, and, the amount of on-the-job training, which are required to competently perform the set of tasks required for that occupation. At ANZSCO3 level, 22 out of 148-unit groups containing more than one skill level, are provided with a broad indication of skill level, while the rest unit groups are at one skill level. An average value of the multiple skill levels provided for those 22 groups was adopted as the according skill score.

The methodology consists of three major stages: 1) data preparation-including data transformation, and variable selection; 2) using unsupervised PAM (partition around medoids) clustering algorithm to analyse datasets made of mixed-typed data; and, 3) comparing different numbers of clusters (k = 2, 3, 4, 5, 6, 7, 8) sequentially to identify any differences between characteristics of the resultant groups and selecting the optimal cluster number via comparing the silhouette width (Handl et al. ,2005) for different numbers of clusters and comparing the dissimilarity of travel behaviour across clusters. Silhouette width measures whether workers that have similar socio-economic traits and occupation type to each other are placed in the same cluster and whether clusters are tightly bound with a substantial distance from each other.

It is important to note that the SEQTS data is stratified, having used a multi-stage clustered sampling technique. The SEQTS 2017-2019 collected travel behavior information from 36,264 respondents living in 14,715 households, with a response rate of 50%. In total, 101,616 trips were recorded. Travel diaries were completed for all members of the household aged five and over, capturing information on all trip stages for each trip. A ‘main mode’ was allocated by the Department of Transport and Main Roads of Queensland Government (DTMR) to each trip, including journey-to-work trips. The ‘main mode’ is the highest mode used on any trip stage in an overall trip, using a hierarchy (from high to low) of public transport modes, then private vehicle travel, then cycling, then walking. If a trip is made by both car and public transport it is categorized as public transport, and so on. The sample included 9,150 workers’ (56% males and 44% females) journey-to-work trip records, with five cases excluded due to abnormally large commutes (>200km). Percentages of employed persons by occupation in our sample and in the Queensland region are provided in Table 1. The comparison between gender split by occupation in our sample and in the SEQ region are shown in Figure 2.

Table 1: Percentage of different occupations in our data sample vs. ABS data in QLD

Occupation type	Sample size	Percentage by occupation (sample data)	Percentage by occupation (QLD ABS data)
MANAGERS	1247	13.50%	12.00%
PROFESSIONALS	2313	25.00%	21.70%
COMMUNITY AND PERSONAL SERVICE WORKERS	955	10.30%	11.20%
CLERICAL AND ADMINISTRATIVE WORKERS	1212	13.10%	14.30%
SALES WORKERS	650	7.00%	10.00%
TECHNICIANS AND TRADES WORKERS	1505	16.20%	13.60%
MACHINERY OPERATORS AND DRIVERS	555	6.00%	5.90%
LABOURERS	712	7.70%	9.70%
MISCELLANEOUS	118	1.30%	1.60%

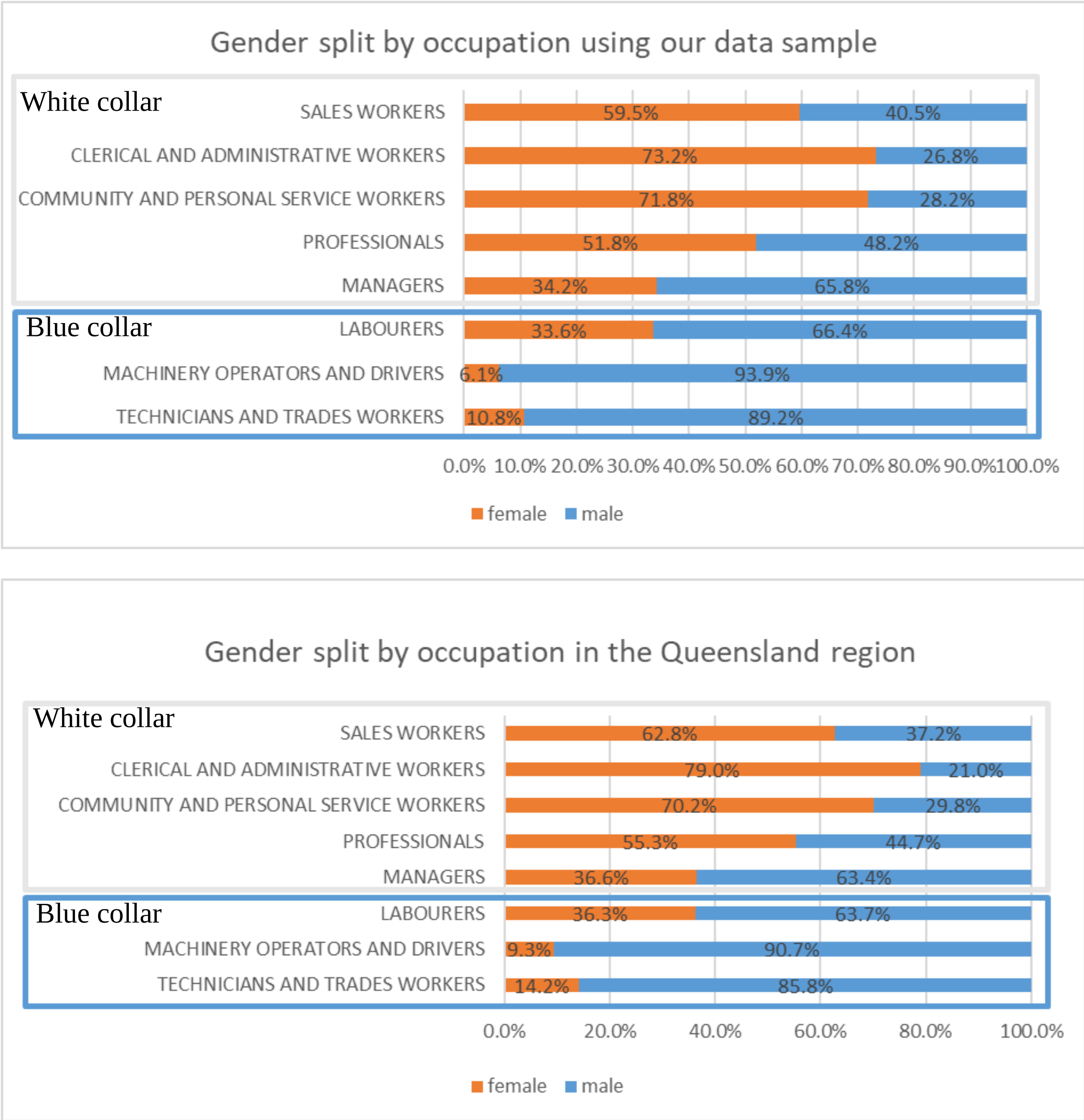

Figure 2. Gender split by occupations (our data sample vs. ABS data in the Queensland region)

4. Result

4.1. Clustering results

Tables 1, 2, and 3 list the identified occupational clusters with the median and mean values within each cluster and their representative occupations at three different numbers of clusters (k = 8, 4 and 3, respectively).

At the most disaggregate level (k = 8), each cluster is dominated by certain industries and occupations (see Table 1). For instance, Group 4 is mostly represented by male laborers in 'other' occupations (i.e., repair and maintenance, personal and other services, etc.). Each cluster shares similar commute mode preferences and similar work trip distances.

As one reduces the level of disaggregation, one can see the merging of these groups in interesting ways, and how the unstructured classification process shifts commuters into different groups when forced to place them in a limited number of bins (i.e., k = 4, k = 3). Interrogating these results one can see that the eight disaggregated commuter types include the more traditional 'blue collar' (Groups 3, 5 and 8), and 'white collar' (Groups 4, 6, 7) groupings. But there are two other distinct female-dominated clusters: community and professional service workers; and, clerical and administrative workers, across the retail and health industries. Interestingly, when aggregated to just six clusters (k = 6), these mostly female community and personal service workers, and clerical and administrative workers, stay almost the same. When further aggregated to only four clusters (k = 4), the two disaggregated female-dominated clusters (Groups 1 & 2 in Table 1) seem to be merged into one single cluster (Group 2 in Table 2). When further aggregated into just three clusters (k = 3), the male-dominated professional workers group and the female-dominated professional workers group in Table 2 seem to merge into one group (i.e. Group 3 in Table 3), which looks more 'white-collar' (64% of Group 3 are females). There remains one female-dominated cluster, which we call 'pink-collar' (86.2% of this group are females), and a more 'blue-collar' cluster (98.2% of this group are males). Details about the median/average value of socio-demographic characteristics and mode share/median trip distance by mode of all these groups (when k = 8, 4, 3) are summarized in Tables 1, 2 and 3, respectively.
With no a priori hypothesis for the appropriate number of clusters to choose for further exploration, we explored the silhouette width result across the resultant clusters when k ranges from 2 to 8. As presented in Figure 3, the difference between the cluster is more distinct when k = 3 than when k = 4, 5, or 6. This gives some confidence that using only three clusters provides a useful and relatively robust segmentation of the commuter dataset. Given that we are exploring a possible employment market segmentation structure for a mode choice model, a lesser number of clusters is valuable for overall model run-time and performance. Hence, the investigation focused on this three-cluster grouping.

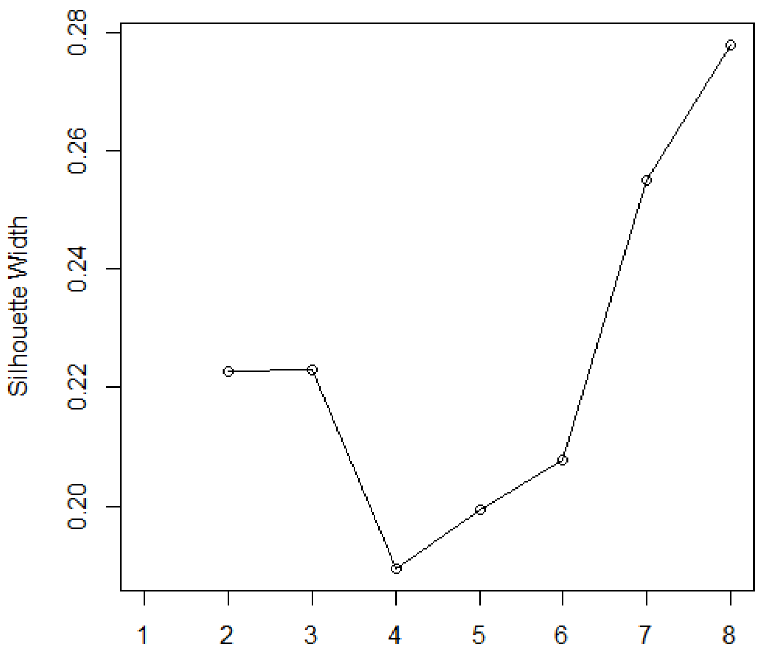

Figure 3. Silhouette width results when clusters size ranging from 2 to 8

Table 2. Summary results at highest level of disaggregation (k = 8)

Cluster	1	2	3	4	5	6	7	8
Age	10(45-49 years)	10(45-49 years)	10(45-49 years)	10(45-49 years)	9(40-44 years)	9(40-44 years)	10(45-49 years)	8(35-39 years)
Sex	Female (931/1017)	Female (1282/1360)	Male (735/755)	Male (841/998)	Male (1453/1536)	Male (1166/1166)	Female (1373/1373)	Male (769/944)
ANZSCO1	Community and profession al service workers (755)	Clerical and administrativ e workers (869)	Machiner y operators and drivers (532)	Managers (964)	Technician s and trades workers (1425)	Professional s (1114)	Professional s (1199)	Labourer s (626)
Industry	Health (490)	Retail (453)	Transport (405)	Constructio n (216)	Constructio n (582)	Education (226)	Education (475)	Other (347)
Household size(median/mean)	3/3.016	2/2.740	3/3.057	3/3.068	3/3.083	3/3.068	2/2.805	3/3.059
Household vehicle number(median/mean)	2/2.293	2/2.242	2/2.291	2/2.354	2/2.345	2/2.148	2/2.183	2/2.144
Bikes(median/mean)	1/1.439	1/1.239	1/1.334	2/1.934	1/1.553	2/1.916	1/1.535	1/1.314
CBD(mean)	0.038	0.118	0.038	0.119	0.0495	0.195	0.115	0.056
Skillscore(median/mea n)	4.0/3.641	3.5/3.663	4.0/4.054	1.50/1.434	3.0/2.884	1.0/1.096	1.0/1.10	4.5/4.603
Mode share of active transport	3.44%	1.70%	0.70%	1.40%	1.60%	5.60%	2.70%	3.40%
Mode share of private motorized vehicle	88.40%	84.10%	94.20%	88.50%	93.90%	76.20%	83.20%	89.80%
Mode share of public transport	7.77%	13.70%	4.60%	9.90%	4.50%	18.00%	13.70%	6.50%
Median trip distance(km) of active transport	0.93	1.23	2.11	5.9	1.94	4.54	1.54	1.285
Median trip distance(km) of private motorized vehicle	10.97	13.115	19.53	17.72	18.795	16.005	13.05	14.255
Median trip distance(km) of public transport	20.61	22.79	18.67	24.45	26.62	19.335	18.71	20.49

Table 3. Summary results at four levels of disaggregation (k = 4)

Cluster	1	2	3	4
Age	8(35-39 years)	10(45-49 years)	10(45-49 years)	10(45-49 years)
Sex	Male (2734/2822)	Female (2052/2342)	Male (2010/2019)	Female (1872/1966)
ANZSCO1	Technicians and trades workers (1429/2822)	Clerical and administrative workers (1038)	Professionals (1045/2019)	Professionals (1268)
Industry	Construction (1005)	Retail (453)	Transport (521)	Health (850)
Household size(median/mean)	3/3.082	3/2.901	3/3.089	2/2.790
Household vehicle number(median/mean)	2/2.312	2/2.253	2/2.237	2/2.172
Bikes(median/mean)	1/1.538	1/1.266	2/1.907	1/1.474
CBD(mean)	0.051	0.094	0.15	0.099
Skill score(median/mean)	3/3.23	4/3.92	1/1.76	1/1.48
Mode share of active transport	1.77%	2.69%	3.52%	2.59%
Mode share of private motorized vehicle	93.34%	84.97%	82.32%	84.99%
Mode share of public transport	4.61%	11.87%	13.97%	12.05%
Median trip distance(km) of active transport	1.765	1.17	6.32	1.49
Median trip distance(km) of private motorized vehicle	17.935	12.185	17.315	13.04
Median trip distance(km) of public transport	22.42	21.875	21.42	18.74

Table 4. Summary results at three levels of disaggregation (k = 3)

Cluster	1	2	3
AGE	9(40-44 years)	9(40-44 years)	10(45-49 years)
SEX	Male (3732/3801)	Female (2060/2391)	Female (1892/2957)
ANZSCO1	Technicians and trades workers (1408/3801)	Clerical and administrative workers (1049/2391)	Professionals (2231/2957)
INDUSTRY	Construction (1090/3801)	Retail (605/2391)	Health (928/2957)
HHSIZE(median/mean)	3/3.1	3/2.9	3/2.9
HHVEH(median/mean)	2/2.3	2/2.3	2/2.2
BIKES(median/mean)	1/1.7	0/1.2	1/1.6
Skillscore(median/mean)	3/3.0	4/3.9	1/1.3
CBD(mean)	6.00%	9.00%	14.00%
Mode share of active transport	63/3793 (1.7%)	61/2379 (2.6%)	111/2947 (3.8%)
Mode share of private motorized vehicle	3512/3793 (92.6%)	2045/2379 (86.0%)	2400/2947 (81.4%)
Mode share of public transport	218/3793 (5.7%)	273/2379 (11.5%)	436/2947 (14.8%)
Median trip distance(km) of active transport	2.08	1.18	2.89
Median trip distance(km) of private motorized vehicle	18.405	12.28	13.75
Median trip distance(km) of public transport	25.765	21.07	19.225

Interrogating further into the three-cluster results, ‘pink-collar’ group is mainly comprised of female clerical and administrative workers (35.85%), community and personal service workers (17.6%), sales workers(15.37%), laborers(8.96%), and male clerical and administrative(7.48%) with a 3.9 average skill score. As depicted in Figure 3., the ‘white/blue collar’ group result in this study stays similar with the conventional ‘white-collar’ and ‘blue-collar’ group, with Managers and Professionals accounting for more than 85% of ‘white-collar’ workers, sharing a 1.3 average skill score and over 98% of ‘blue-collar’ workers being males, mostly working as technicians and trades workers, managers, and machinery operators and drivers, laborers. Distribution of skillscore results across three clusters are both sensible and surprising. In terms of the skill level requirement associated with each of these clusters, the violin plots in Figure 3 suggest a noticeable difference in the distribution of skillscore. Most ‘white-collar’ workers meet the requirement of high levels of knowledge or formal training. ‘Pink-collar’ workers provide a commonly lower level of skill requirement. The skillscore for blue-collar workers seem to be more evenly distributed. In addition, more ‘white-collar’ workers work in the CBD of Brisbane while ‘pink-collar’ and ‘blue-collar’ workers’ job locations are more dispersed in the suburban areas.

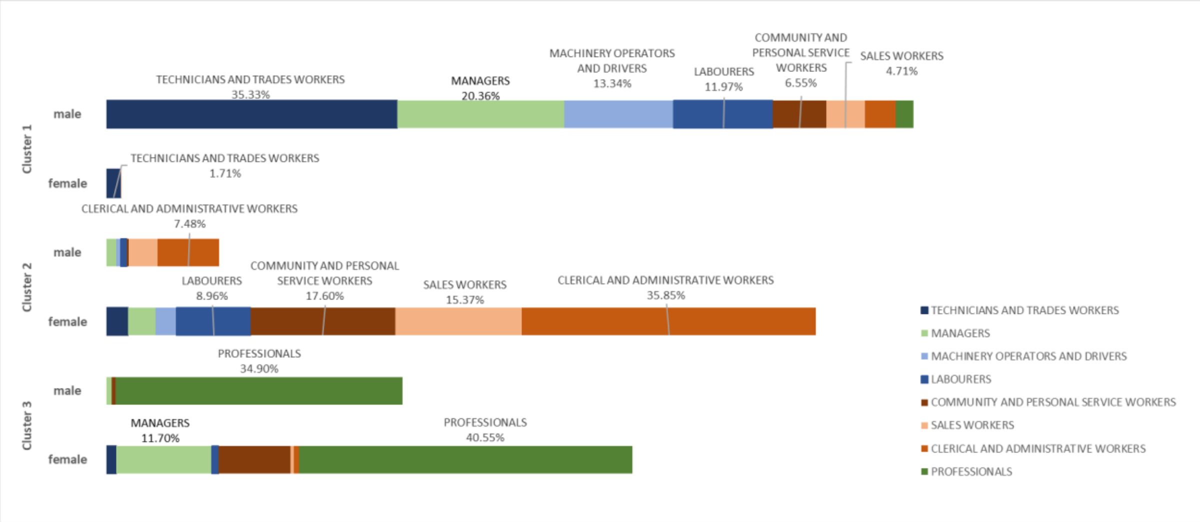

Figure 4. Component analysis of three clusters by gender and occupation

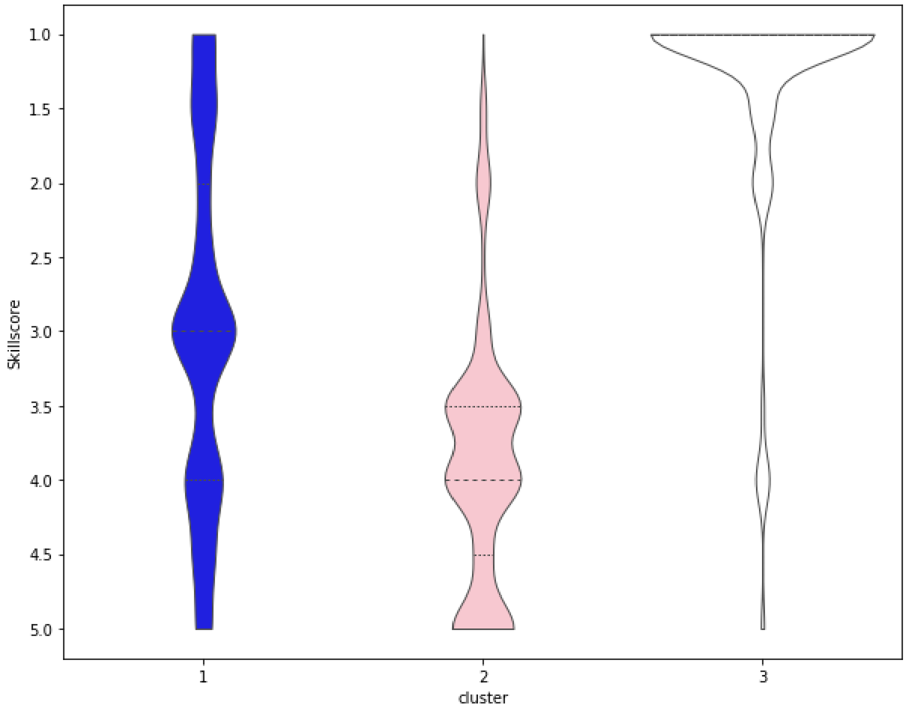

Figure 5. Distribution of skillscore across three clusters

4.2. Comparing mode share and trip distances across three types of workers

To explore RQ2 & RQ3, commuting behaviors of these three major groupings were compared, as shown in Figures 5 and 6. Private motor vehicle is the most frequently chosen mode for commuting across the three groups, albeit with significant differences across the groups: 81.4% for ‘white-collar’ workers; 86% for ‘pink-collar’ workers; and 92.6% for ‘blue-collar’ workers. In terms of median trip distances by private motor vehicle, the ‘white-collar’ workers commuted a shorter trip distance (13.75 km) than ‘blue-collar’ workers (18.405 km) whilst ‘pink-collar’ workers tended to drive the shortest distances (12.28 km). The proportion of white-collar workers using public transportation to the workplace is almost 3 times greater than the blue-collar workers (14.8% versus 5.7%). But blue-collar workers tend to travel very long distances when commuting by public transport as compared to white-collar workers (25.8 km vs 19.2 km, respectively). Pink-collar workers have a modest share of commutes made by public transport (11.5%) but have a similar median trip distance for these trips to white collar workers (21.1 km vs. 19.2km, respectively). For active travel (walk or cycle) the ‘white-collar’ group has the highest percentage of workers using this mode, and their trip distances are almost twice as far as the ‘pink-collar’ group.

These results are in line with previous research on Australian households showing that women often take work closer to home to be closer to schooling and childcare (Baxter et al., 2016, pp. 33-34). The results suggest that commuting behavior between the three clusters are statistically dissimilar and we hypothesise that these observed differences can be taken forward for future research attempting mode choice model reformulations in the BSTM.

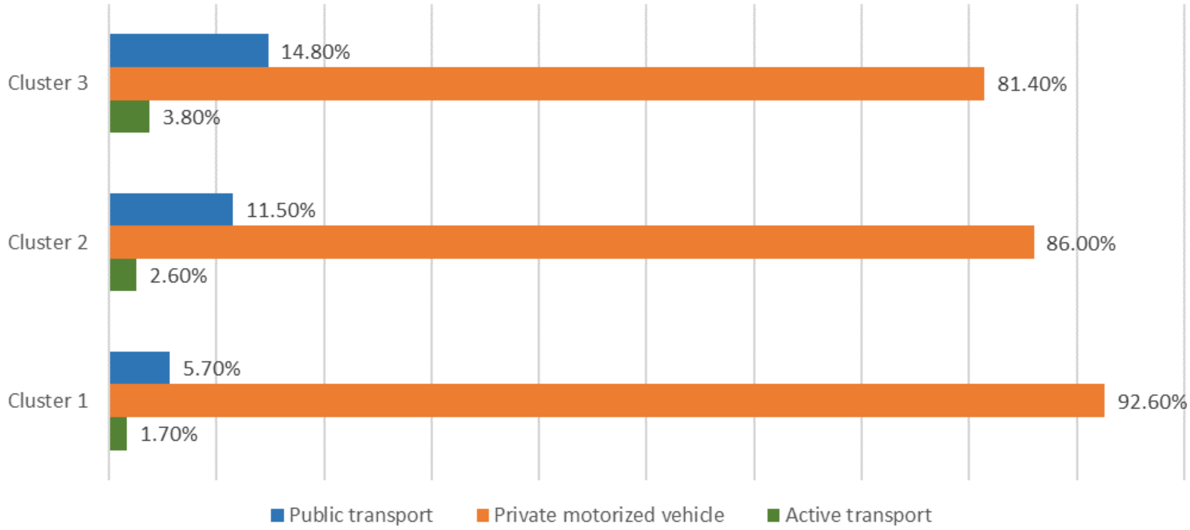

Figure 6. Mode share comparison across three clusters

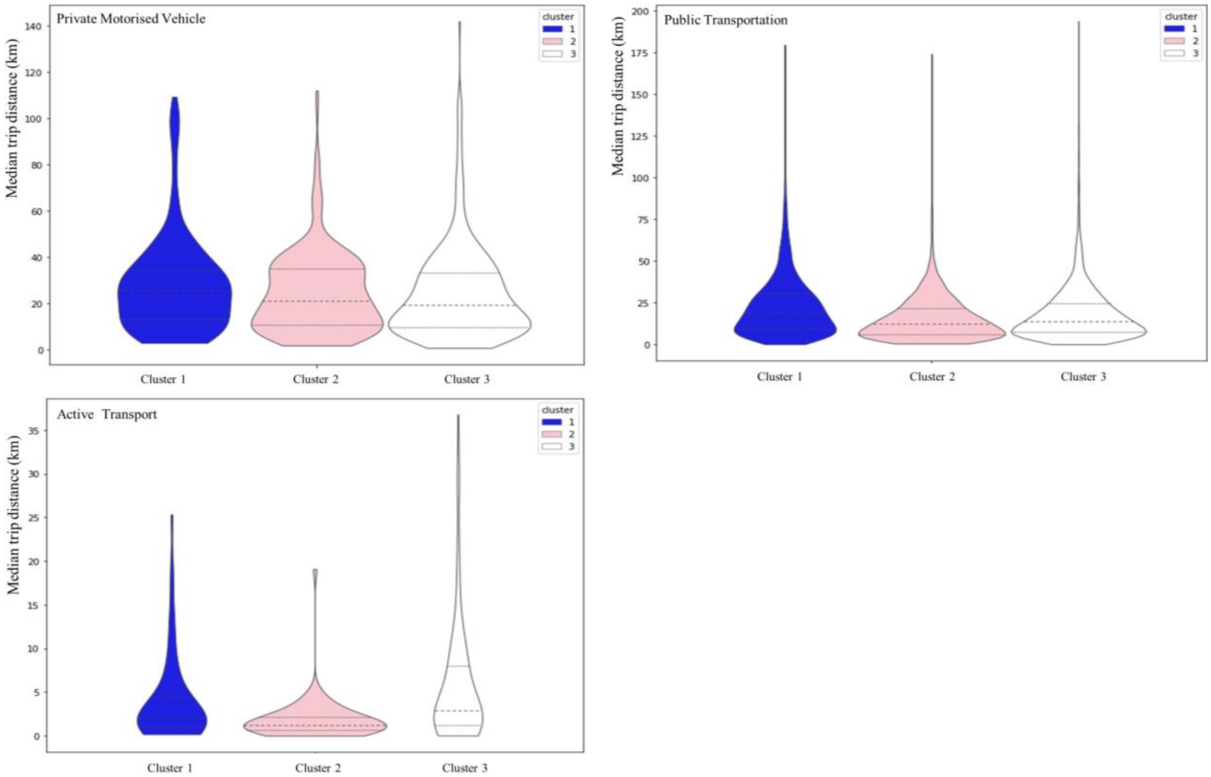

Figure 7. Median trip distance distribution by mode for three clusters

5. Discussion

Given the vexed history of recent Australian travel demand modelling, there is a need to continue to improve the accuracy of city-region transport models, to generate more robust project and network demand forecasting. This paper has made a number of small contributions towards this task.

Methodologically, the paper has shown that inductive clustering techniques can be used to explore commute types at a number of levels (k = 2 to 8) and see what is happening as different groupings are aggregated. In theory, inductive approaches are better suited for this type of analysis as they remove any potential bias of the researcher in making educated hunches as to what improved market segmentation might look like. Our approach would allow each city to explore its own datasets and come up with reasonable and justifiable 'solutions' for the market segmentation problem, regardless of its own peculiar employment market.

One must be cautious in interpreting the results, given that female-dominated or male-dominated clusters and their travel behaviour should not be conflated with the commuting behaviour of men or women, per se. There is nuance needed in taking these results through and operationalising them in mode choice models.

That said, given the heavy dominance of men in the transport planning/engineering field in most nations, the potential for male-bias when using deductive approaches to the market segmentation approach appears high. That women's occupations haven't been further disaggregated, analysed and discussed in the commute modelling literature very often suggests that there might have been issues in the past, that our methods partially overcome.

In applied terms, the results provide strong empirical evidence that the conventional blue/white collar segmentation strategy for transport models fails to sufficiently represent female workers' travel behaviour appropriately, at least in Brisbane. Given the similarities in the employment markets of Brisbane and other Australia and New Zealand cities, it may be time to replicate these methods or find other ways to better incorporate the differences in women's travel behaviour. The results confirm work done in Sydney and other jurisdictions in that a 'pink-collar' grouping is likely worth including in the BSTM. But our approach did not find that a 'gold-collar' grouping (high-end business and finance workers) is needed for Brisbane, despite this grouping's inclusion in the main Sydney model.

There appears significant worth in exploring further the travel characteristics of the two distinct female-dominated clusters of commuters' travel identified in Table 2, which suggests that pink-collar workers are potentially two key groups (shall we say, 'aqua-collar' and 'purple-collar' commuters?). When computing power and transport modelling advances to the point where a higher level of disaggregation is possible without pushing out model run times, it may be of value to include such differentiation in the market segmentation problem. At the present time, however, the benefits of doing so in model accuracy are outweighed by the problems of model complexity and run-time. This is an agenda for future research.

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