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Novel sources of data for monitoring food and nutrition

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Contents

Summary

Monitoring food and nutrition is of significant public health importance. Overall, dietary risks were the third-leading risk factor contributing to the total burden of disease and injury in Australia for 2015. Monitoring requires timely, reliable, consistent and accessible data related to food supply, food purchasing and acquisition, food and physical activity behaviours, and nutritional status.

There are, however, limitations to many of the data sources traditionally used in food and nutrition monitoring. Several of the traditional data sources are infrequently and/or irregularly collected, are subject to various biases, are expensive to collect, and/or have a high participant burden. The increasing creation and collection of data via less traditional means provides opportunities for novel sources that can potentially fill some of these gaps.

This report provides information about novel data sources that could be used for monitoring food and nutrition to guide future use and strengthen the evidence available for policy makers. It includes example analyses of 3 data sources—purchase data, electronic payment data and location data—to highlight the potential uses of, and considerations when using, such data sources.

What are novel data sources?

Novel data sources—in the context of food and nutrition monitoring—are sources of data that were not collected for statistical purposes and are yet to have been extensively used for these purposes. Novel data sources that could be used in food and nutrition monitoring include market share data, purchase data, electronic payment data, location data, and app and wearable device data (Table 1).

What are the potential uses of novel data sources?

The potential uses of novel data sources depend on the data source, with different data sources better suited to different uses. Market share data and location data could contribute to monitoring food supply, while purchase data and electronic payment data could be used in monitoring food purchasing and acquisition. App and wearable device data could be used in both monitoring food and physical behaviours and monitoring nutritional status.

What did the example analyses show?

Comparing novel data sources against traditional data sources can be useful in broadly validating data. Findings from the Australian Bureau of Statistics' Apparent Consumption of Selected Foodstuffs 2018–19 showed that:

- the percentage of energy purchased from discretionary foods (38% in 2018–19) was similar to that reported as consumed in a population nutrition survey (35% in 2011–12)
- there were differences in the relative contributions of macronutrients between energy purchased and consumed which potentially reflect the different scope of the 2 data sources (supermarket purchasing compared with overall diet).

Electronic payment data from 2 of Australia's largest banks were separately analysed to investigate average spending on dining out or fast food, average frequency of dining out or fast food transactions, and average dining out or fast food transaction value. The results of these analyses were difficult to interpret, given differences in use of payment methods over time and between sociodemographic groups, and require careful consideration.

The location of food services (cafes, restaurants, and takeaway outlets), from the Australian Business Register, was used to investigate associations between the density of food services and overweight and obesity. Broadly, Statistical Areas Level 3 (SA3s) closer to capital cities had higher densities of food services than rural areas, although there were exceptions.

What are some of the key considerations when using novel data sources?

Novel data sources can complement, but not replace, more traditional data sources. While some novel data sources offer advantages over more traditional data sources—such as continuous data collection, large sample sizes, prospective and objective data collection, and frequent, regular and timely data provision—there are also limitations. These include issues with data coverage and representativeness, consistency and comparability of definitions, transparency of data collection and analysis methods, and commercial sensitivities.

Given the above, the quality of novel data sources should be assessed for specific research questions and, where possible, the novel data sources should be validated against more traditional data sources. Opportunities to work with the data providers and owners to further develop and standardise the data should also be explored.

Table 1: Novel data sources for monitoring food and nutrition and their potential uses, strengths and limitations

Data source	Potential uses	Potential strengths	Potential limitations
Market share data *Information about the market share of different products and/or companies*	Mainly related to monitoring food supply, including: • monitoring trends in the market share of products or product categories • comparing market share between areas • monitoring contributions of companies (or specific brands) to the food supply • identifying top-selling products or brands	• Provides information about processed foods	• Potential lack of transparency in data collection and/or analysis methods • Potential commercial sensitivities or other restrictions on use and/or publication of data • Analysis below national level may be limited
Purchase data *Information about quantities of food and drink purchased by consumers from retailers*	Mainly related to monitoring food purchasing and acquisition, including: • monitoring trends in purchasing patterns, including evaluating the impact of policy or regulatory changes or health promotion activities • comparing purchasing patterns between areas or population groups, such as remoteness areas or socioeconomic groups • analysing associations between purchasing patterns and health outcomes • monitoring food affordability, including geographic variation • estimating diet quality (with or without linkage to food composition data) • analysing relationship between price and purchasing patterns	• Continuous data collection • Timely data availability • Large sample sizes • Availability of data for small areas • Availability of time series data • Availability of detailed information about purchases • Point-of-sale scanner data: prospective and objective collection of data • May include sociodemographic characteristics from loyalty programs	• Potential lack of transparency in data collection and/or analysis methods • Potential commercial sensitivities or other restrictions on use and/or publication of data • Household scanner data: may be open to bias if participants do not scan all purchases • Point-of-sale scanner data: generally limited to supermarkets and larger stores (currently) • Point-of-sale scanner data: data for loyalty program members may not be representative of the general population • Data reflect purchasing rather than consumption • Absence of data at an individual person level
Electronic payment data *Information about the value and frequency of electronic payments*	Mainly related to monitoring food purchasing and acquisition, including: • monitoring trends in food expenditure • comparing food expenditure by sociodemographic characteristics • analysing associations between food expenditure and health outcomes	• Continuous data collection • Timely data availability • Prospective and objective data collection • Large sample sizes • Availability of data for small areas • Availability of time series data • May include sociodemographic characteristics • Offers coverage of cafes, fast food and restaurants (not available in other sources)	• Potential lack of transparency in data collection and/or analysis methods • Potential commercial sensitivities or other restrictions on use and/or publication of data • Lack of information on what was purchased • Not possible to tell how many people the purchasing is for • Based on electronic payments only and do not include cash and cheque payments

(continued)

Table 1 (continued): Novel data sources for monitoring food and nutrition and their potential uses, strengths and limitations

Data source	Potential uses	Potential strengths	Potential limitations
Location data *Information about the location of features*	Mainly related to monitoring food supply, including: • monitoring changes in food retail environments over time • analysing associations between food retail environments and food behaviours and/or health outcomes • comparing food retail environments between areas or population groups, such as remoteness areas or socioeconomic groups • identifying food deserts (areas with poor access to healthy food options) and food swamps (areas where less healthy food options inundate healthy food options) • evaluating the impact of policy or regulatory changes	• Timely data availability • Large sample sizes • Low burden and cost of data collection • Availability of data for small areas • Availability of time series data	• Potential issues with data coverage • Potential issues with accuracy of data
App and wearable device data *Information about food and drink recorded as consumed and physical activity*	Mainly related to monitoring food and physical activity behaviours and monitoring nutritional status, including: • estimating diet quality or physical activity • analysing associations between diet quality or physical activity and health outcomes • identifying weight loss subgroups • monitoring trends in food and physical activity behaviours, including evaluating the impact of policy or regulatory changes or health promotion activities	• Large sample sizes • Potential for reduced data entry errors • Low participant burden and cost of data collection • Wearable device data: prospective and objective collection of data	• Issues with representativeness as individuals who use apps or wear devices are likely to differ from those who don't • Issues with data quality due to issues such as accidental or deliberate omission of foods and drinks by users, errors in selection of foods and drinks, and errors in estimation of portion sizes • Potential effect of using an app on habitual behaviour • Potential issues with standardisation of food composition databases and/or limited information about classification of foods used in apps • Issues with missing data, due to individuals not always using apps or wearing devices • Issues with accuracy of data, such as step counts, estimates of energy expenditure and heart rate

1 Introduction

The food and beverages people consume play an important role in health. Good nutrition is required for normal growth and development of infants and children, and contributes to healthy weight, quality of life, resistance to infection, and prevention of chronic conditions and premature death for people of all ages (NHMRC 2013).

Conversely, poor nutrition can contribute to poor health. For example, a high intake of saturated fat is linked with coronary heart disease and type 2 diabetes (WHO 2003), while a high intake of processed meat is linked with colorectal cancer (WCRF & AICR 2010). Overall, dietary risks were the third-leading risk factor contributing to the total burden of disease and injury in Australia for 2015, contributing 7.3% of the burden through diseases such as coronary heart disease, type 2 diabetes, stroke and bowel cancer (AIHW 2019a).

The production of the foods and beverages people consume also impacts health. Food production is a major contributor to global environmental changes, such as climate change, biodiversity loss and freshwater use, which then impact the food system and human health, via reduced food security, diminished nutrient content of certain crops, and exacerbated famine, among other impacts (Willett et al. 2019).

Given the roles food and nutrition play in health, their monitoring is of significant public health importance—it can provide information for planning, evaluating and improving policies, programs and services, with the ultimate aim of improving nutrition-related health. However, in order for monitoring to be effective, timely, reliable, consistent and accessible data are required.

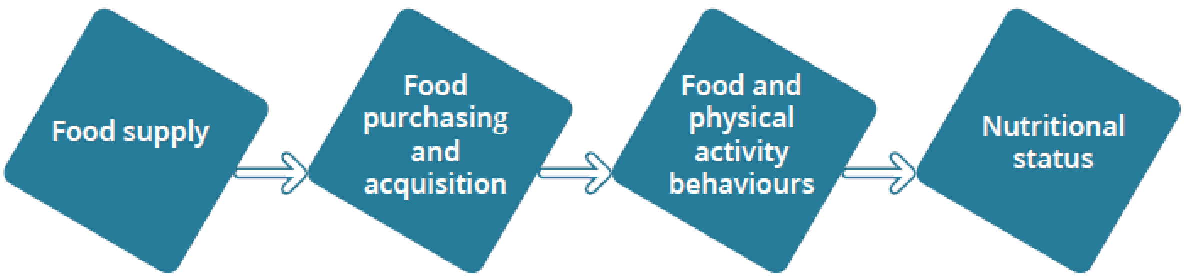
A food and nutrition monitoring framework

The food and nutrition system in Australia extends from food supply and distribution, through to consumption, nutrition and health outcomes and covers a wide range of components, from food production, food processing, imports and exports, to consumer demand, food preferences, price, access, and advertising, among others (AIHW 2012).

Monitoring the food and nutrition system in Australia requires information related to:

- food supply
- food purchasing and acquisition
- food and physical activity behaviours
- nutritional status (Figure 1.1).

Figure 1.1: Framework for a national food and nutrition monitoring system



Source: Masters et al. 2006.

Traditional data for food and nutrition monitoring

There are a range of data sources that have traditionally been used in monitoring each element of the food and nutrition system.

Food supply

Monitoring food supply includes monitoring foodstuffs available for consumption and food composition (Masters et al. 2006). Monitoring foodstuffs available for consumption involves monitoring quantities of foods available (for example, kilograms of fruit available per capita), while monitoring food composition involves monitoring the nutrient and non-nutrient composition of foods.

Historically, the Australian Bureau of Statistics' (ABS) Apparent Consumption of Foodstuffs in Australia collection has been a source of data for foodstuffs available for consumption. The collection traditionally estimated the amount of food from major food groups consumed in Australia, under the assumption that all available foodstuffs were consumed (ABS 2007), and was derived from a range of data sources related to agriculture, livestock, manufacturing, imports and exports. Apparent consumption based on these methods was available at the national level only. The collection was discontinued in 2000 following an ABS review of the sources and resources required to compile reliable data (Masters et al. 2006).

In 2020, beginning with 2018–19 data, the ABS launched a new Apparent Consumption of Selected Foodstuffs series (ABS 2020b). The series is primarily based on point-of-sale scanner data from major supermarkets, marking a significant change in data sources used for apparent consumption and providing an example of the use of a novel data source in the monitoring of food and nutrition. The new series is not directly comparable with the older Apparent Consumption of Foodstuffs in Australia and is described in more detail in 'Chapter 3 Purchase data'.

Food balance sheets, published by the Food and Agriculture Organization of the United Nations, provide an alternate source of data for foodstuffs available for consumption. The balance sheets report per capita supply of various food items available for human consumption, taking into consideration production, imports, exports, non-food uses and losses, among other factors (FAO 2019).

The primary source of food composition data in Australia is Food Standards Australia New Zealand (FSANZ), which generates, compiles and publishes food composition data under the Australian Food Composition Program (FSANZ 2019). Some analytical data are commissioned by FSANZ, while other data are provided by food companies and organisations. The data are compiled and published in electronic databases, such as the Australian Food Composition Database, which provides data for 54 core nutrients, and others as available, for a variety of basic foods and mixed dishes. Release 1 of the Australian Food Composition Database is the most recent reference database, with data preparation completed in 2017.

Gaps and limitations

For many years, there was a gap in food supply data, with the cessation of the ABS Apparent Consumption of Foodstuffs in Australia collection. While it does not fill this past gap and is not directly comparable with the previous collection, the new Apparent Consumption of Selected Foodstuffs series will provide an alternate data series from 2018–19 onwards.

While food balance sheets continue to be published by the Food and Agriculture Organization, there are limitations to these, such as:

- food balance sheets are derived from data from a large numbers of sources (including sample surveys, censuses, administrative records and best estimates) that have been subjected to complex transformations, which complicates quality assurance (FAO 2001)
- while food balance sheets include both primary and processed commodities, information on processed commodities is limited in its specificity
- information is provided at the national level and generally cannot be disaggregated to sub-national levels, so cannot be used to assess food supply for different population groups or geographic areas, which may differ substantially from the national level.

Food purchasing and acquisition

Monitoring food purchasing and acquisition includes monitoring food expenditure, types, price and quantity, as well as food security (Masters et al. 2006).

Information on household expenditure on food has often been sourced from the ABS Household Expenditure Survey (HES), which is conducted every 6 years. Expenditure data are collected from a sample of households, with estimates derived from diaries in which respondents record expenditure across a 2-week period (ABS 2017a). The most recent HES was completed in 2015–16.

Some information on food price is provided by the ABS Consumer Price Index (CPI). The CPI measures the change over time in the price paid by households for selected goods and services, including food (ABS 2019a). Food price information is sourced from supermarkets, restaurants, cafes, and takeaway outlets, with most data now sourced from transaction (scanner) data. CPI data are released every quarter.

The cost of a healthy diet can be monitored using 'food basket' tools that measure the price of a selected basket of foods chosen to reflect a healthy diet. A variety of tools have been developed and used at state, regional and community levels within Australia, which has limited the comparability of data to date and no national survey has been conducted (Lee et al. 2018). Price data for food basket surveys are typically collected in-store from a sample of stores by researchers and/or volunteers.

At a national level, some information on food security was provided by the ABS National Nutrition and Physical Activity Survey (NNPAS) 2011–12. Adult survey respondents were asked if there was any time in the last 12 months that they, or members of their household, had run out of food and couldn't afford to buy more (ABS 2013b). Respondents who answered yes were asked if they, or members of their household, had gone without food. The NNPAS is not part of a regular survey program. Although some information on food security was also collected in the ABS National Nutrition Survey (NNS) 1995 and National Health Survey (NHS) 2001, it is not directly comparable with the information collected in the NNPAS. In 2019, funding was announced for an Intergenerational Health and Mental Health Study, which will include nutrition (Department of Health 2019). The study is expected to be conducted in 2023–24, with data released from 2025. Information about whether information on food security will be collected is not yet publicly available.

Gaps and limitations

There is a lack of current and regular data related to food expenditure in Australia. The HES is conducted every 6 years, leaving interim periods during which current data are unavailable. Estimates from the survey are based on a sample of the Australian population—the sample is designed to allow accurate analysis at the state level, which may restrict analysis at finer levels of geography. A further limitation of the HES is that the classification used was not designed primarily for public health purposes, meaning it may not be possible to distinguish products within a category that are nutritionally distinct (for example, both sugar-sweetened drinks and diet drinks are included in the 'soft drinks' category). The HES also lacks information about quantities (mass or volume) of foods purchased.

While CPI data are released every quarter, consumer price indexes often relate to selected individual foods only and may not relate to the cost of a total diet (Lee et al. 2018). Data related to the cost of a total diet, such as those collected using 'food basket' tools, have not been collected at a national level and there is limited comparability of data collected at state, regional and community levels (Lee et al. 2018). Data collection is often from a sample of stores and can be resource-intensive, including relying on volunteer contributions.

There is also a lack of current national-level data related to food security in Australia, with the most recent national-level data collected in the NNPAS 2011–12, the National Aboriginal and Torres Strait Islander Health Survey 2012–13 and the National Aboriginal and Torres Strait Islander Nutrition and Physical Activity Survey 2012–13. The measure used to collect the data in these surveys is also likely to result in an underestimate of food insecurity (McKay et al. 2019).

Food and physical activity behaviours

Data for monitoring food and physical activity behaviours have typically been sourced from population nutrition surveys.

The most recent source of nationally representative comprehensive food and physical activity behaviour data is the ABS NNPAS 2011–12. The NNPAS 2011–12 collected a variety of data from those aged 2 and over, including data from 24-hour dietary recalls of food, beverages and supplements on 2 separate days, as well as data on usual dietary behaviours, and whether respondents were currently on a diet and for what reason (ABS 2013b). A range of physical activity data were collected, including self-reported data and pedometer steps. As mentioned, the NNPAS is not part of a regular survey program. The Intergenerational Health and Mental Health Study, which will include nutrition, is expected to be conducted in 2023–24, with data released from 2025. Before the NNPAS 2011–12, the next-most-recent comprehensive nationally representative surveys were the ABS NNS 1995 and the Australian National Children's Nutrition and Physical Activity Survey in 2007.

Short survey questions related to food and physical activity behaviours have previously been used to provide information on specific food and physical activity behaviours. The ABS NHS 2017–18 included short questions related to fruit and vegetable consumption (usual daily serves and whether consumption had increased or decreased since the same time the previous year), sugar-sweetened and diet drink consumption (usual frequency and amount consumed) and physical activity (ABS 2019b). The NHS has been conducted around every 3 years, although questions have sometimes varied between surveys.

Gaps and limitations

Comprehensive national-level food and physical activity behaviour data are infrequently collected in Australia, leaving interim periods during which current data are unavailable. This is likely related to the expense of conducting comprehensive nutrition surveys. There is also a high participant burden in the collection of comprehensive food behaviour data. The combined expense of conducting such surveys and high participant burden potentially reduce sample sizes and decrease response rates.

While data are collected from short survey questions more frequently, results based on 24-hour dietary recalls and short survey questions can vary. For example, based on 24-hour dietary recall data from the NNPAS 2011–12, 26% of males aged 19–50 and 20% of females aged 19–50 met recommended fruit intake guidelines (ABS 2016b). Although relating to a slightly different age group and to both males and females, data based on a short survey question ('How many serves of fruit do you usually eat each day?') in the Australian Health Survey 2011–12 indicated that 49% of Australians aged 18 years and over met recommended fruit intake guidelines (ABS 2013a).

Data from both 24-hour dietary recalls and short survey questions are subject to various biases. For example, data collected from nutrition surveys are subject to potential under-reporting of food intake, due to:

- actual changes in diet that participants may make when they know they will be surveyed
- misrepresentation (whether deliberate, unconscious or accidental) to make diets appear healthier or to make diets quicker to report (ABS 2014).

Nutritional status

While dietary data collected in surveys can be used to compare nutrients with Nutrient Reference Values and identify inadequate or excessive intakes, biological measures are needed to assess the extent of the health effects of these on a population (Masters et al. 2006).

Nationally representative data for biological measures of nutritional status have previously been sourced from the ABS National Health Measures Survey (NHMS) 2011–12 (a voluntary component of the Australian Health Survey 2011–12). The NHMS 2011–12 collected urine samples from participants aged 5 and over and blood samples from those aged 12 and over (ABS 2013b). The survey provides data for a range of nutrient biomarkers, such as iron, folate, iodine and vitamin D, as well as chronic disease biomarkers, such as markers of diabetes and cholesterol. The NHMS is not part of a regular survey program, however, the recently announced Intergenerational Health and Mental Health Study is expected to include biomedical data collection when it is conducted in 2023–24, with data released from 2025.

Measured height, weight, waist circumference and blood pressure data have been sourced from various ABS surveys, including the NNS 1995, NHS 2007–08, Australian Health Survey 2011–12, NHS 2014–15 and NHS 2017–18.

Gaps and limitations

Nationally representative surveys of biological measures are expensive to undertake and are conducted infrequently—the NHMS was conducted in 2011–12 and is not part of a regular survey program. Surveys of biological measures can also have a high participant burden by requiring attendance at a clinic to collect urine and/or blood samples, which may decrease response rates. As participation is often voluntary (such as in the NHMS), samples may have biases towards participating groups. In the NHMS 2011–12, participants were reimbursed $50 for travel, child-care and/or time off work to maximise response rates.

Novel data for food and nutrition monitoring

The above discussion of the traditional data sources used in food and nutrition monitoring has highlighted some of the key data gaps and limitations. Several data sources are infrequently and/or irregularly collected, subject to various biases, are expensive to collect, and/or have a high participant burden. With the increasing creation and collection of data via less traditional means, less traditional data sources provide a novel potential data source to fill some of these gaps. In the context of food and nutrition monitoring, novel or less traditional data sources are sources of data that were not collected for statistical purposes and are yet to have been extensively used for these purposes.

These data sources include data such as purchase data, which could provide information on food purchasing and acquisition, and app and wearable device data, which could provide information on food and physical activity behaviours, among others.

This report

The remainder of this report provides information about novel data sources for monitoring food and nutrition to guide future use and strengthen the evidence available for policy makers:

- Chapters 2 to 6 each focus on a different type of data—namely market share data, purchase data, electronic payment data, location data, and app and wearable device data—and provide information about the potential uses of such data (including examples of use) and a broad assessment of the strengths and limitations of the data for monitoring food and nutrition.
- Chapter 7 provides details of analyses conducted using 3 of these novel data types—purchase data, electronic payment data and location data—as a demonstration of how these data could be used and to highlight factors to consider when completing and interpreting such analyses. Supplementary figures (Figures A1–A5) examining differences in purchase data and electronic payment data across Primary Health Network (PHN) areas are presented in Appendix A.
- Chapter 8 provides an overall conclusion and recommendations on the use of novel data sources in monitoring food and nutrition.

The report does not discuss other considerations in the use of novel data sources such as ethical and legal considerations around privacy and data ownership, or data access considerations, such as the computing power required for the analysis of big data or costs of accessing and analysing data, as these considerations are beyond the scope of this report.

2 Market share data

What are market share data?

Market share data provide information about the market share of different products and/or companies (that is, the proportion of the market made up by different products and/or companies).

Depending on the source, the data may include information in units, volumes or weights or in monetary values. The ‘market’ in market share data may vary—it may relate to the entire food market of a country, or to a specific section of the market, such as the supermarket market, convenience store market or foodservice market.

There are limited publicly available details of how market share data are collected. Based on what is available, a number of data sources are collated to produce market share data.

Who provides market share data?

Potential providers of market share data include market research companies.

Potential uses

Market share data can be used on their own or combined with food composition databases to allow analysis of available energy and nutrients.

Market share data can be used to report on the ‘food supply’ element of the food and nutrition monitoring system (Figure 1.1).

The potential uses of market share data in food and nutrition monitoring include:

- monitoring trends in the market share of products or product categories
- comparing market share between areas
- monitoring contributions of companies (or specific brands) to the food supply
- identifying top-selling products or brands.

Measures based on units, volumes, weights, monetary values or available energy and nutrients may have different interpretations and implications. Comparisons of measures based on monetary values can by influenced by variation in price between brands, between areas or over time. The market share of a company or brand based on monetary values may not reflect its contribution to available energy or nutrients.

Measures that are based on food composition and available energy and nutrients require mapping of market share data to food composition databases. This is likely to be an ongoing process, given the continual introduction of new products to the market and possible changes to existing products (such as reformulation).

Trends in market share or comparisons of market share between areas can be correlated with sociodemographic factors, health risk factors and/or health outcomes.

Examples of use

A number of studies across a number of countries have analysed market share data—a selection of these are described below to demonstrate some of the potential uses.

Monitoring contributions of brands and companies to the food supply

Researchers from PepsiCo used market share data to monitor the contribution of food and beverage companies to the food supply globally and within certain countries in 2009 and 2010 (Alexander et al. 2011). Ten major multinational companies had made commitments to improve the nutritional quality of their products and around advertising of products to children. The study sought to understand the impact these commitments may have by analysing the market share (based on value defined by retail selling prices) of companies. Based on analysis of data from Euromonitor (a commercial data provider), the study found that the top 10 companies made up 15.2% of global food sales. The authors suggested that this meant the top 10 companies made up only a small proportion of global food sales and that, as such, the impact of public health commitments from the 10 multinational companies that had made commitments may be limited without similar commitment by small- and medium-sized companies who also contributed to the market. The study did not consider the market share of companies based on available energy and nutrients, which may have produced different results.

Analysing associations between sales patterns and health outcomes

Euromonitor data were used in another study to explore the relationship between soft drink sales and obesity and diabetes (Basu et al. 2013). The study estimated the association between per capita soft drink sales and the prevalence of obesity and diabetes in 75 countries, controlling for differences between countries in age, sales of other foods, income and urbanisation. Soft drink sales were averaged across a number of years to reflect that the risks of overweight and diabetes are related to sustained exposure to unhealthy foods, rather than an instantaneous effect. The study found soft drinks sales were strongly correlated with the prevalence of obesity, with every 1% increase in soft drink sales associated with an extra 2.3 in every 100 adults being obese. Soft drink sales were also correlated with diabetes prevalence.

Identifying top-selling products or brands

Researchers from Deakin University and the Commonwealth Scientific and Industrial Research Organisation estimated the impact of mandatory folic acid fortification of bread-making flour in Australia on folic acid intake among women of childbearing age using a series of theoretical models (Emmett et al. 2011). To produce an accurate estimate of folic acid intake, the researchers used market share data from Retail World to identify the top-selling brands of foods voluntarily fortified with folic acid, along with nutrition information panel information about folic acid content. Using these data along with population nutrition survey data, and a series of predictive models, the researchers estimated the impact of folic acid fortification at different levels, and with different education programs, use of supplements and consumer behaviours, on the number of women who would meet recommended intakes.

How could the findings be used?

Policy makers and program developers could use the findings of analysis of market share data to identify products that may be suitable targets for reformulation (such as reduction of sodium, added sugar and/or saturated fat content), taxation, marketing restrictions, or education campaigns.

These data could also be used to evaluate public health nutrition interventions, such as those listed above (that is, reformulation, taxation, marketing restrictions, or education campaigns).

Data quality

Assessment of the data quality of market share data will differ depending on the research purpose and data source.

A potential lack of transparency in market share data collection and/or analysis methods is a key limitation of the data for all research purposes. Bandy and colleagues (2019) highlighted that the reliability and accuracy of data from the market research company Euromonitor are open to question because exact sources of data are not made available. Similarly, for all research purposes, there may be commercial sensitivities or other restrictions on use and/or publication of data.

The use of market share data has an advantage over more traditional data sources for monitoring of the food supply as it provides information about processed foods (historic apparent consumption data relate mainly to primary foods prior to processing). However, as the level of data collection is generally for an overall market, which may cover a large geographic area (for example, the supermarket market for all of Australia), analyses for smaller geographic areas may be limited.

3 Purchase data

What are purchase data?

Purchase data provide information about the quantities of food and drink purchased by consumers from retailers such as supermarkets.

Depending on the source, the data may include information about units, volumes or weights purchased, the cost of items purchased, whether items purchased were on promotion, the location of purchases, the date and time of purchases, loyalty program information, and sociodemographic information about purchasers.

Purchase data include:

- point-of-sale scanner data, which are collected from products scanned at retail checkout counters
- household scanner data, which are collected by members of a sample of households who scan items purchased by the household using apps or scanners provided by the researcher/s; households also typically provide sociodemographic information to the researcher/s.

Who provides purchase data?

Potential providers of purchase data include individual retailers, such as supermarkets, as well as data analytics companies.

Potential uses

Purchase data can be used on their own or combined with:

- food composition databases to allow analysis of available energy and nutrients
- loyalty program data to allow analysis by sociodemographic characteristics, such as age, sex or area of residence.

Purchase data can be used to report on the ‘food purchasing and acquisition’ element of the food and nutrition monitoring system (Figure 1.1).

The potential uses of purchase data in food and nutrition monitoring include:

- regular monitoring of trends in purchasing patterns, which may enable the ongoing evaluation of the impact of policy or regulatory changes or health promotion activities
- comparing purchasing patterns between areas or population groups, such as remoteness areas or socioeconomic groups
- analysing associations between purchasing patterns and health outcomes
- monitoring food affordability, including geographic variation
- estimating diet quality, based on food composition
- analysing relationship between price and purchasing patterns.

Measures based on units, volumes, weights or expenditure are suited to different uses. Expenditure-based measures reflect spending—rather than units, volumes or weights of items purchased—and comparisons can be influenced by variation in price between areas or over time (including that caused by price competition, drought or natural disasters). As such, they may be better suited to research questions related to food expenditure or affordability, rather than estimates of diet quality. Interpretation of expenditure-based measures may need to consider differing prices of nutritionally similar products (for example, ‘premium’ versus ‘non-premium’ products), and how purchasing of these products may vary between areas or over time.

Measures based on food composition and nutrients purchased can be used to estimate diet quality. They require mapping of purchase data to food composition databases, which is likely to be an ongoing process, given the continual introduction of new products to the market and possible changes to existing products (such as reformulation). Interpretation of measures based on food composition and nutrients purchased may need to consider that changes over time can be influenced by both deliberate changes by consumers in purchasing of different foods and by changes to foods by manufacturers (which consumers may or may not be aware of).

More generally, measures based on proportions (such as the proportion of total energy purchased provided by a certain food or food group) can be influenced by changes in both the numerator and the denominator (Tin Tin et al. 2007). For example, a change in the proportion of total energy purchased provided by discretionary foods could reflect a change in the amount of energy purchased from discretionary foods, a change in the total amount of energy purchased, or a combination of both.

When analysing associations between purchasing patterns and health outcomes, the time-based relationship between exposure to dietary factors and the health outcomes of interest needs to be considered. Consideration also needs to be given to other sources of food not covered by the data source being used, as well as non-food factors that can influence health and behaviour such as socioeconomic status.

Examples of use

A number of studies across a number of countries have analysed purchase data—a selection of these are described below to demonstrate some of the potential uses.

Example analyses using purchase data are included in ‘Chapter 7: Example analysis 1’, and highlight some of the complexities of these data and considerations required when using them.

Monitoring trends in purchasing patterns

Colchero and colleagues (2016) used household scanner data to evaluate changes in purchasing of sugar-sweetened beverages in Mexico after implementation of an excise tax in January 2014 on non-dairy and non-alcoholic beverages with added sugar. Monthly volumes purchased were calculated for 2 years before and 1 year after implementation of the tax, with households classified into socioeconomic groups based on annual questions related to assets and education. A model was used to adjust for pre-existing trends and other variables affecting beverage purchasing over time. The study found that monthly volumes of taxed beverages purchased were on average 6% lower in 2014 compared with expected purchases had the tax not been implemented. There were greater reductions in low socioeconomic households.

Comparing purchasing patterns between population groups

Household scanner data collected in Britain were used to explore differences in purchasing based on socioeconomic position (Pechey et al. 2013). The study analysed data from take-home food and beverage purchases from all sources for 25,674 households in 2010. Households were categorised into 3 groups based on the occupation of the head of the household: higher managerial and professional; white collar and skilled manual; and semi-skilled and unskilled manual. Food and beverage products were classified into 43 categories, with each category classified as 'healthier', 'neutral' or 'less healthy'. Regression analysis was used to determine the proportion of total energy purchased from each category and purchasing of nutrients by socioeconomic position. In 28 of the 43 categories there were statistically significant differences between socioeconomic groups. Proportionally less energy came from healthier food categories, and proportionally more energy from less healthy food categories, for the lower socioeconomic group than the higher socioeconomic group.

Monitoring food affordability

The ABS used point-of-sale scanner data to compare the average annual rate of price change of various food groups with the CPI (ABS 2016c). An Australian Dietary Guideline Price Index was constructed to measure long-term change in food and beverage prices. The study classified foods and beverages from the CPI fixed basket of goods into 7 food groups based on the Australian Dietary Guidelines—grains and cereals, vegetables, fruit, milk and alternatives, meats and alternatives, discretionary, and oils and fats. Prices of all food groups increased from 2001 to 2014 with 4 food groups increasing faster than the CPI. Vegetables experienced the greatest average annual rate of price change (3.8%), ahead of fruit (3.0%), discretionary foods (3.0%) and oils and fats (2.9%).

Estimating diet quality

More recently, the ABS used point-of-sale scanner data, alongside household expenditure data, to estimate apparent consumption of selected foods in Australia in 2018–19 (ABS 2020b). Aggregated scanner data from major supermarkets (provided to the ABS by the supermarkets for use in the CPI) were used to directly estimate quantities of food purchased, while data from the HES 2015–16 were used to estimate quantities of food available for consumption that were not captured by the scanner data. The estimates cover food and non-alcoholic beverages purchased from the food retail sector, excluding restaurant meals and takeaway and fast foods. The data were largely defined using the 2011–13 AUSNUT database, which allows similar analyses to those using population nutrition survey data. Key findings included that apparent consumption of fruit and vegetables was below that recommended in the Australian Dietary Guidelines, that apparent sodium consumption far exceeded recommended intake, and that 38.2% of purchased energy came from discretionary foods. Seasonal differences in purchasing of some products were also apparent. Ongoing data releases are expected.

On a smaller scale, a New Zealand study compared major sources of macronutrients from purchase data for February 2004 to January 2005 from a single store with those from 2 national nutrition surveys conducted in 1997 and 2002 (Hamilton et al. 2007). Food composition data were sourced for the top-selling 3,000 food and non-alcoholic products purchased, using brand-specific data where possible. The purchase data and nutrition survey data showed broadly similar proportional contributions of total fat, saturated fat and carbohydrate to energy. The major food sources of energy, total fat, saturated fat and carbohydrate, and their percentage contributions to these, were also similar between the purchase data and 1 or both of the surveys. The authors suggest that purchase data can supplement national nutrition surveys in monitoring nutrition, but highlighted that it may not be possible to estimate absolute nutrient intakes from purchase data, because data are often not available for the number of people purchased for, or their age or sex.

How could the findings be used?

Purchase data can be used for routine monitoring of purchasing trends and behaviours and the nutritional quality of purchased foods. It can also be used to monitor purchasing of specific categories of foods, for example, core foods or discretionary foods.

Policy makers and program developers could use the findings of the analysis of purchase data to identify products that may be suitable targets for reformulation (such as reduction of sodium, added sugar and/or saturated fat content), taxation, marketing restrictions, or education campaigns.

These data could also be used to evaluate public health nutrition interventions, such as those listed above (that is, reformulation, taxation, marketing restrictions, or education campaigns). It could also be used to assess food affordability between regions.

Given purchase data are available for small areas and are often collected continuously, these activities could be tailored to local areas and use current data.

Data quality

Assessment of the data quality of purchase data will differ depending on the research purpose and data source.

Mapping of purchase data to food composition databases is time consuming and an ongoing process, given the continual introduction of new products to the market and possible changes to existing products (such as reformulation). Where the purchase data is already aggregated, there is the potential for a lack of transparency in analysis methods and/or the data definitions or categories used. In addition, commercial data providers may restrict the publication of detailed methods (Bandy et al. 2019). There may also be commercial sensitivities or other restrictions on use and/or publication of data. For example, retailers may or may not be willing to share data for research of negative health consequences from retail sales (Morris et al. 2018).

Despite this, strengths of both point-of-sale scanner data and household scanner data relevant to many research purposes include continuous data collection, timely data availability, large sample sizes, the availability of data for small areas, the availability of time series data and the availability of detailed information about purchases. A strength of point-of-sale scanner data is the prospective and objective collection of data.

If used for monitoring of food purchasing and acquisition, data coverage and representativeness are potential limitations of purchase data. More specifically:

- Point-of-sale scanner data are generally limited to supermarkets and do not capture purchasing from markets, restaurants, takeaway outlets, convenience stores or smaller speciality stores (such as bakeries, butchers and greengrocers). Supermarkets and grocery stores accounted for the majority (62%) of food retailing turnover in Australia in 2017–18 (defined as expenditure for supermarket and grocery stores; liquor retailing; other specialised food retailing; cafes, restaurants and catering services; and takeaway food services) (ABS 2019d). However, this may differ for different foods, between different locations and groups and over time.
- If point-of-sale scanner data are from 1 retailer or retail chain only, they may not be representative of purchasing from all retailers in that sector.

- Point-of-sale scanner data for loyalty program members may not be representative of the general population. However, without loyalty program member information, purchases cannot be attributed to individual purchasers, and therefore cannot be associated with individual-level sociodemographic characteristics.
- Household scanner data may be open to bias if the sample is not representative and/or if participants do not scan all purchases.

If used for monitoring of food behaviours (such as food intake), a key limitation of purchase data is that they reflect purchasing rather than consumption—the data do not account for food wasted or otherwise not eaten. For example, meat products often have a portion of fat or bone that is inedible but, unless adjusted for, is still included in the calculation of energy and nutrients by weight. The impact of this is again likely to differ for different foods, between different groups and over time.

The absence of data at the individual person level may also be a limitation for monitoring of food behaviours.

4 Electronic payment data

What are electronic payment data?

Electronic payment data provide information on the value and frequency of electronic payments (such as transactions made using credit and debit cards).

Depending on the source, the data may include information about transaction amounts (in $), the merchant, the location of transactions, the date and time of transactions, and sociodemographic information about the account holder.

Merchant information may include the merchant name, merchant category code (a code assigned to a merchant by a bank when the merchant first accepts payments using these cards), and Australian and New Zealand Standard Industrial Classification (ANZSIC) code (a code that reflects a business entity's main activity).

Electronic payment data include:

- acquirer data, which are data collected by the bank that allows a merchant to accept card payments (for example, the bank that provides a merchant with a terminal). Acquirer data provide data for all transactions for the merchant but will only provide sociodemographic information for transactions by cardholders whose cards were issued by the same bank
- issuer data, which are data collected by the bank that issues a card to a cardholder. Issuer data provide data for all transactions by cardholders from the issuer and include sociodemographic information. In some cases, issuer data can also provide information about cardholder income.

Who provides electronic payment data?

Potential providers of electronic payment data include banks and payment processing companies, as well as data analytics companies.

Potential uses

Electronic payment data can be used to report on the 'food purchasing and acquisition' element of the food and nutrition monitoring system (Figure 1.1).

The potential uses of electronic payment data in food and nutrition monitoring include:

- monitoring trends in food expenditure
- comparing food expenditure by sociodemographic characteristics
- analysing associations between food expenditure and health outcomes.

Possible measures used in the analysis of electronic payment data include the:

- average transaction value, calculated as the total value of all transactions divided by the total number of transactions
- average transaction frequency, calculated as the total number of transactions divided by the total number of customers, for a given time period
- average spend per customer, calculated as the total value of all transactions divided by the total number of customers, for a given time period.

Examples of use

There are few examples of the use of electronic payment data for monitoring food and nutrition, or for health statistics uses more broadly.

Example analyses using electronic payment data are included in 'Chapter 7: Example analysis 2a' and 'Example analysis 2b', and highlight some of the complexities of these data and considerations required when using them.

Monitoring trends in food expenditure

While not necessarily prepared for food and nutrition monitoring purposes, the Commonwealth Bank of Australia (CBA) previously reported how much its customers were spending on fast food and restaurants, including how this had changed over time and how it differed by sociodemographic characteristics (Commonwealth Bank 2017). Average monthly spending on fast food was reported to have increased by 20% from 2015 to 2017. The analysis highlighted some of the difficulties in analysing the data, such as being unable to tell how many people the purchases are for—customers aged 40–45 had the highest monthly spend on fast food, with it noted that they may be purchasing meals for a family.

Cardlytics, a commercial data provider, used card and direct debit data to report that eating out represented 9% of consumers' spending in the United Kingdom in 2017, which was an increase from 7% in 2015 (Cardlytics 2017).

Neither of these examples of use appear to have accounted for possible changes in payment method over time (such as a shift from cash to card payments).

How could the findings be used?

The findings of analysis of electronic payment data could be used to inform the development of food and nutrition-related policies, programs and interventions. For example, analysis by age group and establishment (such as cafe, restaurant, fast food or takeaway) could identify groups for targeted nutrition education programs.

These data could also be used to evaluate public health nutrition interventions, such as nutrition education programs.

Data quality

Assessment of the data quality of electronic payment data will differ depending on the research purpose and data source.

A potential lack of transparency in electronic payment data analysis methods and comparable data definitions, are possible limitations. There may also be commercial sensitivities or other restrictions on use and/or publication of data.

Despite this, strengths of electronic payment data relevant to many research purposes include continuous data collection, timely data availability, prospective and objective data collection, large sample sizes, the availability of data for small areas and the availability of time series data. Electronic payment data also offers coverage of cafes, fast food and restaurants (not yet available in sources such as purchase data).

If used for monitoring of food purchasing and acquisition, a lack of information on what was purchased (and therefore the nutritional quality of what was purchased) is a key limitation of electronic payment data. Similarly, it is not possible to tell how many people the purchasing is for.

Data coverage is another key limitation of electronic payment data for use in monitoring of food purchasing and acquisition. Electronic payment data are based on electronic payments only and do not include cash and cheque payments. As such, analysis over time or between sociodemographic groups may need to consider differences in the use of cards as a payment method. The relative use of cards also differs by transaction size and merchant category. Survey data released by the Reserve Bank of Australia show that:

- while the majority of purchase transactions in 2016 were debit and credit card payments (52%), more than a third were cash payments (37%)
- the percentage of payments made by card has increased over time (from 26% in 2007 to 31% in 2010, 43% in 2013 and 52% in 2016)
- the increase in the relative use of cards has been largest for lower-value transactions, with the median value of card payments decreasing from $40 in 2007 to $28 in 2016
- the most notable increase in the relative use of cards between 2013 and 2016 was for smaller food retailers, reflecting increased acceptance by merchants of contactless cards for smaller transactions and changes in customer preferences
- the percentage of payments made with cash has decreased over time for consumers of all ages and incomes, however, cash use is generally higher among older individuals than younger individuals and among households with lower incomes than among households with higher incomes (Doyle et al. 2017).

Finally, if electronic payment data are from 1 bank or institution only, they may not be representative of all electronic payments. While it may be possible to weight the data to better represent the population of interest, this is reliant on collection and accuracy of sufficient demographic characteristics in the data set.

5 Location data

What are location data?

Location data, also known as geographic or geospatial data, provide information about the location of features, such as food outlets or green spaces.

Depending on the source, the data may include addresses and/or coordinates, names of features and opening hours.

Some of the other data sources discussed in this report also contain information about location. For example, purchase data may include information about the location of retailers (where purchases were made), while electronic payment data may include this information as well as information about the address of customers.

Who provides location data?

Data can be accessed through retail databases, publicly available web mapping services, national mapping agencies, national statistics agencies, business registers and local food enforcement agencies.

Potential uses

Location data can be used to report on the ‘food supply’ element of the food and nutrition monitoring system (Figure 1.1).

The potential uses of location data for monitoring food and nutrition include:

- monitoring changes in food retail environments over time
- analysing associations between food retail environments and food behaviours and/or health outcomes
- comparing food retail environments between areas or population groups, such as remoteness areas or socioeconomic groups
- identifying food deserts (areas with poor access to healthy food options) and food swamps (areas where less healthy food options inundate healthy food options)
- evaluating the impact of policy or regulatory changes.

Possible measures used in the analysis of location data include density, variety and proximity (Ni Mhurchu et al. 2013; Thornton et al. 2009). Using food outlets as an example, measures of:

- density include simple counts of outlets within a specified area as well as counts per population or per square kilometre
- variety include counts of the number of different types of food outlets within a specified area
- proximity include distance or travel time between outlets and other locations, such as schools.

When analysing associations between food retail environments and health outcomes, the time-based relationship between exposure to the food retail environment and the health outcomes of interest needs to be considered.

Examples of use

A number of studies across a number of countries have analysed location data—a selection of these are described below to demonstrate some of the potential uses.

Example analyses using location data are included in 'Chapter 7: Example analysis 3', and highlight some of the complexities of these data and considerations required when using them.

Identifying food deserts

Location data from various sources for Baltimore, United States, were used to identify 'food deserts', which were defined as areas having a distance of more than a quarter of a mile (approximately 400 metres) to a supermarket or alternative; a median household income at or below 185% of the Federal Poverty Level; over 30% of households having no vehicle availability; and a low average Healthy Food Availability Index score (a measure of the presence of staple whole foods and healthy options in food stores) for all food stores. The City of Baltimore used the results to offer tax credits to food retailers to open in food deserts (Behrens Buczynski et al. 2015).

Comparing food retail environments between population groups

Location data obtained from a public corporation (Ordnance Survey) for England were used in the development of the Food Environment Assessment Tool. The interactive mapping tool visualises the spatial distribution of a range of food retail outlets and can be used to identify neighbourhoods with high densities of food outlets, low densities of food outlets, the diversity of outlets available and changes in the type of food outlets over time (University of Cambridge 2017).

Assessing fast food proximity to home and schools and frequency of food purchasing among adolescents

A study conducted in 2006 and 2007 in London, United Kingdom, and Ontario, Canada, among adolescents in grades 7 and 8 (aged 11–13 years) analysed the adolescents' home and school food environments to determine whether proximity to fast food outlets influenced frequency of purchasing from those food stores. Data on the locations of fast food outlets and convenience stores were sourced from local business directories and validated by phone calls, field surveys and inspection of aerial photos. A questionnaire assessed food activity behaviour. Students living within a 1 kilometre distance of a fast food outlet or convenience store were more likely to purchase food from 1 of those food stores at least once a week (He et al. 2012).

Analysing associations between food retail environments and food behaviours and health outcomes

The NHS 2017–18 included information about the proximity of supermarkets, fast food outlets and amenities to survey participants (ABS 2018b, 2019c). The data were sourced from the Public Service Mapping Agency and a commercial data provider (HERE Technologies). Analysis showed no difference for adults in consumption of sweetened drinks, fruit or vegetables by proximity to supermarkets or fast food outlets. However, adults living within 1,500 metres of a supermarket were less likely to be obese than those living further from a supermarket. Similarly, adults living within 1,500 metres of a fast food outlet were less likely to be obese than those living further from one. A number of areas for further analysis or improvement were identified, including refinement of distance measures and investigating use of private vehicles to access supermarkets and fast food outlets.

How could the findings be used?

Policy makers and program developers could use the findings of analysis of location data to identify areas with poor access to healthy food options and/or high exposure to less healthy options. This information could be used to inform interventions to increase access to healthy food options and/or decrease exposure to less healthy options, such as land use restrictions, incentive schemes for retailers to provide healthy options, and creation of community gardens.

Location data may need to be supplemented with other data to understand how food choices are shaped by access and exposure to different food options. Other factors to consider include the reasons for living in an area (for example, work or family reasons), other local amenities (for example, gyms or walking trails) and the sociodemographic characteristics of the residents (Sacks et al. 2019). Additionally, people may choose to use amenities outside of their local area or have easy access to food options in other locations—for example, on their journey to or from work or school.

Data quality

Assessment of the data quality of location data will differ depending on the research purpose and data source or collection method.

If used for monitoring of food supply, data coverage is a potential limitation of location data. Depending on the data source, data may be limited to certain food outlets only (for example, only major fast food chains and not independent outlets), so may not provide an accurate representation of food access. Similarly, for food outlets, outlets may open and close rapidly, such that data may be out-of-date or not reflect current food access. The seemingly increasing popularity of food delivery services (particularly where outlets deliver to wider areas) may also need to be considered when drawing conclusions about food access. Depending on the source of the data, the classification of outlets into industries may not be accurate—for example, in data sourced from a business register, the business may self-assign the industry it belongs to.

When compared with data collected by field observation, the accuracy of food outlet location data from secondary sources varies by the data source, as well as the type of food outlet and geographic characteristics (Fleischhacker et al. 2014). This reinforces the need for separate quality assessment of individual data sources and for different research purposes.

Despite this, strengths of location data relevant to many research purposes include timely data availability, large sample sizes, low burden and cost of data collection (if data use is secondary), the availability of data for small areas and the availability of time series data.

6 App and wearable device data

What are app and wearable device data?

App and wearable device data are types of personally generated health data. Data from software applications (apps) can provide information on the foods and drinks recorded as consumed by users. Data from apps and wearable devices (such as pedometers, accelerometers, heart rate monitors or other wrist-worn activity trackers) can provide information on physical activity.

Depending on the source, food-related data from apps may include generic foods and drinks, branded foods and drinks, creation of dishes from recipes, photographs and/or scanning of barcodes. How portion sizes are entered varies between apps and can be based on measures such as spoons, cups or slices, or on weight or volume estimation. Some apps incorporate food composition databases.

Physical activity-related data from apps and wearable devices may include step counts, distance travelled, activity type, activity duration, heart rate, estimated energy expenditure, and global positioning system (GPS) data.

Other data collected by apps can include sociodemographic and anthropometric data.

Who provides app and wearable device data?

Potential providers of app and wearable device data include app developers and device manufacturers.

Potential uses

App and wearable device data can be used to report on the 'food and physical activity behaviours' and 'nutritional status' elements of the food and nutrition monitoring system (Figure 1.1).

The potential uses of app and wearable device data in monitoring food and nutrition include:

- estimating diet quality or physical activity
- analysing associations between diet quality or physical activity and health outcomes
- identifying weight loss subgroups
- monitoring trends in food and physical activity behaviours, including evaluating the impact of policy or regulatory changes or health promotion activities.

Examples of use

A number of studies across a number of countries have analysed app and wearable device data—a selection of these are described below to demonstrate some of their potential uses.

Estimating diet quality

Few, if any, studies appear to have involved secondary use of data already collected by apps to estimate diet quality. Instead, studies have often compared data collected by apps with data collected by traditional methods, such as 24-hour dietary recall or food diaries, for individuals recruited for a study.

In 1 of these studies, 43 adults who were not regular users of MyFitnessPal (a food-logging app) recorded their dietary intake over 4 days in the app and completed 2, 24-hour dietary recalls administered by researchers (Chen et al. 2019). Compared with the dietary recall data, the app data significantly underestimated energy intake and intake of all macronutrients.

Analysing associations between physical activity and health outcomes

A large study analysed data from 68 million days of physical activity for over 700,000 users (across more than 100 countries) who used a smartphone app that tracked physical activity (Althoff et al. 2017). The analysis showed that the level of variation in the distribution of step counts between individuals within a country was a stronger predictor of the obesity rates of a country than the average step count of a country. As an example, while the United States and Mexico had similar average daily step counts, the United States had a wider distribution of step counts and a higher obesity rate.

Identifying weight loss subgroups

A United States study used data from a weight loss app, in which diet, exercise and weight were recorded, to identify groups that were successful at losing weight, and the characteristics of these groups (Serrano et al. 2016). Classification and regression tree analysis were used to identify 3 subgroups and their characteristics. ‘Occasional users’, who weighed in fewer than 6.5 times were the least likely to lose weight, while ‘power users’, who weighed in at least 6.5 times and logged food for at least 40 days were the most likely to lose weight. The study highlighted some of the challenges of using data from apps—subsamples of data were used for analysis due to constraints on computing memory and users of the app differed from a nationally representative sample.

Evaluating the impact of infrastructure changes on physical activity behaviours

An Australian study evaluated the usefulness of data from the GPS tracking smartphone app Strava for evaluating the impact of infrastructure improvements on cycling behaviour (Heesch & Langdon 2016). The authors concluded that Strava data could be useful for evaluating the short-term impact of infrastructure improvements at a single location. However, the data were less useful for exploring differential changes across locations because of differences in Strava use across locations. Other potential issues included issues with the representativeness of users of the app and with the precision of GPS signals. The authors recommended that the data be used together with more traditional data sources (such as intercept surveys that stop cyclists while they are cycling).

How could the findings be used?

Policy makers and program developers could use the findings of analysis of app and wearable device data to identify population groups (based on sociodemographic data) with poor food and/or physical activity behaviours who may be the target of interventions.

These data could also be used to evaluate public health interventions, such as health education programs or changes to infrastructure.

Data quality

Assessment of the data quality of purchase data will differ depending on the research purpose and data source.

The strengths of app and wearable device data relevant to many research purposes include large sample sizes, potential for reduced data entry errors (compared with data entry errors that may occur with traditional food behaviour collections), and low participant burden and cost of data collection (if data use is secondary). A strength of wearable device data is prospective and objective collection of data.

However, there are a number of potential limitations of app and wearable device data for many research purposes, including issues with:

- representativeness of the data, as individuals who seek out apps to help them monitor their food intake or who wear activity trackers are likely to differ from those who do not
- quality of data due to issues such as accidental or deliberate omission of foods and drinks by users, errors in selection of foods and drinks, and errors in estimation of portion sizes (Chen et al. 2019)—however, the prevalence of misreporting with apps has been found to be similar to that with 24-hour dietary recalls (Ambrosini et al. 2018)
- the effect of using an app on habitual behaviour—for example, the use of an app to record foods and drinks consumed may have effects on consumption, which may mean that the data collected do not reflect habitual food intake (Maringer et al. 2018)
- the quality of the underlying food composition databases used in apps, which is not always known (Maringer et al. 2018)
- missing data, due to individuals not always using apps or wearing wearable devices
- accuracy of data, such as step counts, estimates of energy expenditure and heart rate (Feehan et al. 2018; Reddy et al. 2018).

7 Example analyses

This chapter provides examples of how 3 novel data sources—purchase data, electronic payment data, and location data—could be used for monitoring food and nutrition.

The examples are provided primarily as a demonstration, rather than to claim specific findings from the analyses. The findings from the analyses should be interpreted bearing in mind the specific limitations of these data outlined in each section and in Box 7.1. This chapter includes some analyses examining associations between electronic payment data and location data with overweight and obesity by PHN area. These are supplemented by further figures examining variations in electronic payment data by PHN area in Appendix A. As with the information provided in this chapter, these figures are provided primarily as a demonstration.

Access to data is an important consideration in the potential use of novel data sources. Due to the complexities involved in accessing raw, unit record purchase data and electronic payment data for analysis, the analyses presented in this chapter were conducted by the data providers and not by the AIHW, with the exception of the correlational analyses with overweight and obesity by PHN and Statistical Area Level 3 (SA3) areas. Analyses of location data were also completed by the AIHW.

Box 7.1: Correlations with overweight and obesity

The electronic payment data and location data were compared with area-level measures of overweight and obesity. Overweight and obesity is influenced by a complex interplay of individual, environmental, and societal factors.

In addition to the considerations and limitations noted for each of the example analyses, it should be noted that:

- Where data were correlated, this does not imply causation (in either direction). In many instances, there are likely to be other factors related to both the variable of interest and overweight and obesity, such as socioeconomic position or remoteness area.
- Correlations were based on area-level data (PHN area and SA3 region). Different results may be seen with data for a differing geographic level or for individual-level data.
- Overweight and obesity estimates are based on survey data from the NHS 2017–18 and are subject to their own limitations. Survey data are based on a sample of the population and so may differ from results that would have been found if the entire population were included and are also potentially subject to other biases.
- The SA3 region overweight and obesity data are modelled crude rates derived from modelled estimates of the number of adults who were overweight and obese in each SA3 in 2017–18 (PHIDU 2020) and SA3 Estimated Resident Population data for adults in June 2017. These should be treated as indicative of the likely prevalence of overweight and obesity in a region only. At an SA3 level, the ability to show the extent of the variation that exists between geographical areas is limited (PHIDU 2020).

- Modelled estimates were unavailable for areas with a population under 1,000; with a high proportion of the population in non-private dwellings, *Very remote* areas, or discrete Aboriginal communities; and areas with a high error rate for the estimate.
- The demonstration data and overweight and obesity data were reviewed for normal distribution using the Shapiro-Wilk test for normality, Q-Q (quantile-quantile) plots and histograms. If the variables being correlated were normally distributed, a Pearson's correlation was used (r); otherwise a Spearman's Rank correlation was used (r_s). Significant correlations ($p < 0.05$) were described in strength as either weak ($r = 0.25$), moderate ($r = 0.50$) or strong ($r = 0.70$).
- Different results may have been seen if a different health outcome (such as prevalence of overweight or obesity alone, or prevalence of abdominal overweight or obesity) were used.

Example analysis 1: Purchase data

The analyses of purchase data in this section are from the ABS Apparent Consumption of Selected Foodstuffs 2018–19 (ABS 2020b).

General methods

Data source

This data source contains aggregated point-of-sale scanner data (purchase data) from Australia's major supermarket chain retailers. These supermarkets accounted for an estimated 82% of the Food Retail sector (ABS 2020b). The scanner data are provided to the ABS to help improve the measurement of consumer price change for the quarterly Consumer Price Index (CPI).

The scanner data comprises the Stock Keeping Unit (SKU) of the sales item, a description of the item, the geographical region and weekly aggregate amounts of the quantity and value of the sales. The data used in this report did not include liquor purchasing. Data are included for the 2018–19 financial year, however, trend information will be available with subsequent releases.

The 2015–16 Household Expenditure Survey (HES) is used to help estimate and add the value of product sales which are not captured by the major supermarkets. This includes food purchases made at convenience stores, butchers, fish shops, bakeries, delis and vegetable markets. The HES is used to estimate the ratio of expenditure in stores not represented by the scanner data to expenditure from the major supermarkets for a given food group in a given geographical area (Greater Capital City Statistical Areas (GCCSAs)).

Mapping to food composition data

The SKU for each food item was assigned a code from FSANZ's Australian Food, Supplement and Nutrient Database (AUSNUT) 2011–13 based on the product description. The AUSNUT classifies foods into major (2-digit), sub-major (3-digit) and minor (4- or 5-digit) groups based on its key ingredient (an example for the classification of non-alcoholic beverages is shown in Table 7.1). There are 24 major food groups, 132 sub-major food groups and over 500 minor food groups (FSANZ 2016).

Table 7.1: Classification of foods and dietary supplements, AUSNUT 2011–13

11	**Non-alcoholic beverages**
113	**Fruit and vegetable juices, and drinks**
11301	Fruit juices, commercially prepared
11302	Fruit juices, freshly squeezed
11303	Fruit juices, fortified
11304	Vegetable juices
11305	Vegetable juices, freshly squeezed
11306	Fruit and vegetable juice blends
11307	Fruit drinks (ready to drink or made from concentrate)
11308	Vegetable drinks
11309	Fruit drink, prepared from dry powder

Source: (FSANZ 2016).

The AUSNUT 2011–13 contains comprehensive nutrient data for each food and non-alcoholic beverage, as well as information to allow these to be allocated to, and assessed against, food groups from the Australian Dietary Guidelines (for example, grams and serves). This means that, in theory, these data can be used for similar food and nutrient analyses as a national nutrition survey to evaluate population level means (ABS 2020b). AUSNUT coding was performed on around 95% of the total value of the scanner data foods in the 2018–19 period.

Food expenditure data from the 2015–16 HES were also mapped to a set of 63 food groups from the AUSNUT.

Per capita measures

Mean daily per capita amounts were derived by dividing the annual total amount of a food or nutrient purchased by the December 2018 Estimated Resident Population, and then dividing by 365 (ABS 2020b).

The ABS also created average recommended serves of the 5 food groups from the 2013 Australian Dietary Guidelines that takes into consideration the size of the population in each age and sex group, to compare against the mean daily per capita amounts.

General considerations for interpretation of purchase data analysis

The following considerations apply to several of the example analyses presented in the following text and should be kept in mind when interpreting the data.

Data coverage

The scanner data in conjunction with the HES represents the majority of the food available for consumption in Australia, however, they do not capture:

- fast foods, cafe and restaurant meals
- meals provided by institutions that source food from the non-retail sector
- home grown or produced food
- wild harvested/hunted bush food or seafood
- alcohol.

There is also no adjustment for waste—food organic waste from households was estimated to be around 3.1 million tonnes in 2016–17. To put this in context, it was estimated that 14.1 million tonnes of foods and non-alcoholic beverages was purchased in 2018–19 (ABS 2020b). Additionally, all food and non-alcoholic beverages purchased in a particular year are assumed to have been consumed in that year.

The AUSNUT 2011–13 coding also has a number of limitations, including:

- it was developed for the 2011–13 Australian Health Survey (ABS 2013b) and reflects the food supply and preparation practices for that time period
- it is indicative of the nutrient levels in a particular food or dietary supplement for products available during the 2011–13 Australian Health Survey only—the nutrient composition of foods and ingredients can vary due to a number of factors so may not reflect the most current nutrient profile

- it was designed to code foods reported as consumed in the dietary recall components of the 2011–13 Australian Health Survey, however, many foods purchased from supermarkets require preparation. The AUSNUT does contain some nutrient data for unprepared foods (for example, uncooked pasta, flour, jelly crystals, uncooked cuts of meat) and these were used as appropriate (FSANZ 2016).

Comparisons with other data sources

Where possible, findings from novel data sources have been compared with those from more traditional data sources to assess their ability to complement population nutrition surveys. There are, however, some differences between the sources that should be noted.

Results from the ABS Apparent Consumption of Selected Foodstuffs were compared with population nutrition survey data from the NNPAS 2011–12. Noteworthy differences between the 2 sources include that:

- purchase data reflect purchasing, while population nutrition survey data reflect consumption—some items that are purchased may not be consumed within the relevant time period, or at all
- purchase data do not capture food obtained through other avenues, which would be captured by a population nutrition survey
- population nutrition survey data are susceptible to social desirability bias and under-reporting, and under-reporting is unlikely to affect all foods and nutrients equally (ABS 2013b)
- the data relate to different time periods.

There are a range of other factors which are likely to influence food purchasing and which may contribute to observed changes over time or differences between areas. These could include differences in availability of food retailers and of the foods and beverages available within retailers, differences in access (economic and/or physical) to foods and beverages, and differences in prices, placements, promotions and other in-store factors. Supermarket chains may also differ the format of, and products available in, stores based on area demographics—for example, stocking 'high-end produce and ready-to-go meal options' in higher socioeconomic areas (Hatch 2019).

Example analysis: Energy purchased from discretionary foods

Discretionary foods are foods and drinks that are not necessary to provide the nutrients the body needs (NHMRC 2013). Many of these foods are high in saturated fats, sugars, salt and/or alcohol. According to the Australian Dietary Guidelines, discretionary foods should only be consumed sometimes and in small amounts—while they can contribute to the overall enjoyment of eating, if their intake is not reduced, there needs to be a substantial increase in physical activity by most Australians to counter the additional energy that comes from these foods. It should be noted that these purchase data exclude alcohol, which is considered a discretionary food.

In this analysis, purchase data were analysed to measure the percentage of total energy purchased provided by discretionary foods. This analysis provides an example of how purchase data can be used to estimate diet quality.

Results

Discretionary foods (foods and non-alcoholic beverages combined) provided more than one-third (38%) of the mean daily per capita energy purchased in 2018–19, or around 3,346 of 8,770 kilojoules.

The percentage of energy purchased provided by discretionary foods can be compared with data from more traditional data sources used for measuring food behaviours, such as population nutrition surveys, to broadly validate the data. These comparisons should, however, be considered in light of the key differences between purchase data and population nutrition survey data highlighted in the 'General considerations for interpretation of purchase data analysis' section above.

The overall total daily energy reported as consumed in the 2011–12 NNPAS was slightly lower than for the purchase data (8,522 compared with 8,770 kilojoules) (ABS 2014). There are a number of reasons why these figures may not be an accurate representation of foods consumed or purchased (see 'General considerations for interpretation of purchase data analysis'*).*

Despite these differences, the findings from the purchase data and population nutrition survey data for discretionary foods are very similar—38% of the energy purchased in 2018–19 was provided by discretionary foods, while 35% of total daily energy reported as consumed in the NNPAS 2011–12 was from discretionary foods (ABS 2014).

Recommendation

The above comparisons suggest that, overall, the relative purchasing of discretionary foods and non-discretionary foods from supermarkets (as measured using purchase data) are similar to the relative consumption of discretionary foods and non-discretionary foods in overall diets (as measured using population nutrition survey data).

This suggests that purchase data could be used to complement population nutrition survey data for monitoring of energy provided by discretionary foods. The availability of purchase data for small areas would further enhance its usefulness by allowing public health nutrition interventions to be tailored to local areas using current data.

Example analysis: Acceptable macronutrient distribution ranges

Unlike micronutrients (that is, vitamins and minerals), macronutrients (protein, fat and carbohydrate) contribute to energy intake (NHMRC 2019). Imbalances in the relative proportions of energy intake provided by macronutrients can increase the risk of chronic disease and affect micronutrient intake.

The Acceptable Macronutrient Distribution Ranges (part of the Nutrient Reference Values; NHMRC 2019) provide recommended ranges of percentages of energy intake for each of the macronutrients for otherwise healthy people to reduce the risk of chronic disease while ensuring adequate micronutrient status. The Acceptable Macronutrient Distribution Ranges are:

- protein: 15–25% of energy
- fat: 20–35% of energy
- carbohydrate: 45–65% of energy.

In this analysis, purchase data were analysed to measure the percentage of energy purchased provided by each of the macronutrients. It provides an example of how purchase data could be used to estimate diet quality at the population level.

Results

In 2018–19, 16% of total energy purchased was provided by protein, 39% by fat and 44% by carbohydrate (ABS 2020b).

The percentage of energy purchased provided by each macronutrient can be compared with data from more traditional data sources used for measuring food behaviours, such as population nutrition surveys, to broadly validate the data. These comparisons should, however, be considered in light of the key differences between purchase data and population nutrition survey data highlighted in the 'General considerations for interpretation of purchase data analysis' section above.

Data from the NNPAS 2011–12 show that, excluding energy provided by alcohol and fibre, around 18% of energy reported as consumed was provided by protein, around 33% by fat, and around 48% by carbohydrate (ABS 2014).

Recommendation

The above comparisons suggest that, overall, the macronutrient distribution of foods purchased from supermarkets differs slightly from the macronutrient distribution of foods consumed in overall diets. This is likely, in part, to reflect that some foods are purchased in large quantities but generally only consumed in small quantities each time (for example, fats and oils).

These limitations should be considered if purchase data are used to complement population nutrition survey data for monitoring of adherence to recommended Acceptable Macronutrient Distribution Ranges.

Example analysis: Leading contributors to purchased energy, saturated fat and sodium

Saturated fat intake is associated with increased plasma low-density lipoprotein cholesterol, which is an established risk factor for coronary heart disease, while sodium intake is associated with increased blood pressure (NHMRC 2013).

The Australian Dietary Guidelines recognise that people eat foods, not nutrients, and so recommend limiting intake of foods containing saturated fat and added salt, rather than limiting intake of saturated fat and salt per se.

In this analysis, purchase data were analysed to determine the foods contributing the most to purchased energy, saturated fat and sodium. It provides an example of an analysis that could be useful for policy or program development and evaluation to identify products that may be suitable targets for reformulation.

Results are available by major and sub-major food groups, however, sub-major groups are presented here to better identify the foods contributing most to purchased energy, saturated fat and sodium.

Results

In 2018–19, the leading contributors to purchased energy were *regular breads, and bread rolls (plain/unfilled/untopped varieties)* and *dairy milk (cow, sheep and goat)* (Table 7.2).

Table 7.2: Leading contributors to purchased energy, 2018–19

Rank	Food group	Per cent of total energy (%)
1	Regular breads, and bread rolls (plain/unfilled/untopped varieties)	6.7
2	Dairy milk (cow, sheep and goat)	5.8
3	Flours and other cereal grains and starches	5.3
4	Beef, sheep and pork, unprocessed	4.5
5	Plant oils	4.4

Source: ABS 2020b.

In 2018–19, the leading contributors to purchased saturated fat were *cheese* and *dairy milk (cow, sheep and goat)* (Table 7.3).

Table 7.3: Leading contributors to purchased saturated fat, 2018–19

Rank	Food group	Per cent of total saturated fat (%))
1	Cheese	10.6
2	Dairy milk (cow, sheep and goat)	9.6
3	Chocolate and chocolate-based confectionery	7.4
4	Beef, sheep and pork, unprocessed	6.2
5	Butters	5.1

Source: ABS 2020b.

In 2018–19, the leading contributors to purchased sodium were *herbs, spices, seasonings and stock cubes* and *regular breads, and bread rolls (plain/unfilled/untopped varieties)* (Table 7.4).

Table 7.4: Leading contributors to purchased sodium, 2018–19

Rank	Food group	Per cent of total sodium (%)
1	Herbs, spices, seasonings and stock cubes	23.1
2	Regular breads and bread rolls (plain/unfilled/untopped varieties)	8.5
3	Processed meat	8.1
4	Gravies and savoury sauces	7.5
5	Cheese	5.0

Source: ABS 2020b.

The leading contributors to purchased energy, saturated fat and sodium can be compared with data from more traditional data sources used for measuring food behaviours, such as population nutrition surveys, to broadly validate the data. These comparisons should, however, be considered in light of the key differences between purchase data and population nutrition survey data highlighted in the 'General considerations for interpretation of purchase data analysis' section above.

These differences likely contribute to some of the differences in the leading contributors to energy between the purchase data for 2018–19 and the NNPAS 2011–12 data. The leading contributors for the NNPAS 2011–12 data were *mixed dishes where cereal is the major ingredient* (9.9%), *regular breads, and bread rolls (plain/unfilled/untopped varieties)* (7.7%) and *dairy milk (cow, sheep and goat)* (4.3%) (ABS 2014).

The *mixed dishes where cereal is the major ingredient* category includes foods such as pizza, sandwiches and filled rolls, and burgers, which are readily available through sources other than supermarkets. That this category makes up a higher percentage of energy in the NNPAS 2011–12 data than in the purchase data likely reflects the inclusion of food from these sources in the survey data. In addition, purchase data reflect foods as purchased, while NNPAS 2011–12 data reflect foods as consumed. A home-prepared dish could therefore be reflected differently between data sources—for example, it would appear as its individual ingredients in purchase data and as a mixed dish in the NNPAS 2011–12.

Similar considerations in interpretation and comparison apply to saturated fat and sodium—the leading contributors for saturated fat for the NNPAS 2011–12 were *mixed dishes where cereal is the major ingredient* (9.9%), *dairy milk (cow, sheep and goat)* (8.4%) and *cheese* (7.2%), while the leading contributors for sodium for the NNPAS 2011–12 were *mixed dishes where cereal is the major ingredient* (14.6%), *regular breads, and bread rolls (plain/unfilled/untopped varieties)* (12.7%) and *processed meat* (6.0%) (ABS 2014).

Recommendation

The above comparisons suggest that, overall, the key sources of energy, saturated fat and sodium purchased from supermarkets differ somewhat from the key sources of energy, saturated fat and sodium in overall diets.

However, knowledge of the leading contributors to energy, saturated fat and sodium purchased from supermarkets has other potential uses, such as identifying foods that may be targeted for reformulation or taxation or that may be the focus of education campaigns. Additionally, purchase data can be used to monitor supermarket purchasing of energy, saturated fat and sodium over time or to compare trends by different population groups.

Example analysis 2a: Electronic payment data

The analyses of electronic payment data in this section were completed by the data provider. The AIHW completed the correlation analysis of electronic payment and overweight and obesity data.

General methods

Data source

This data set contains de-identified customer-level data for electronic payments from the 1 of the 4 largest banks in Australia (based on share of assets held on banks' domestic books).

Data for 2015–2018 were used for this report.

The data relate to credit and debit card transactions, including EFTPOS transactions, BPAY transactions and direct debit transactions. They include age, gender, Statistical Area Level 1 (SA1) location (based on customer mailing address), transaction text, amount, date, time and terminal information (including merchant category code and text identifying the merchant).

Primary and secondary cardholders aged 15 and over were included. Age, gender and SA1 location data were available for each separate primary and secondary cardholder—this may not be the case in other sources of electronic payment data.

Weighting to the general Australian population

As customers in the electronic payment data may differ from the general Australian population, the data were weighted to better represent the general Australian population. Age and location (at the SA2 level) data from the customer data and the ABS Estimated Resident Population data were used to weight the data and adjust the results.

Only customers who spent sufficiently to reflect total spending (based on the number of transactions) were included. Business customers, and non-business customers with similar spending patterns to businesses (identified by outlier transaction patterns), were excluded. The AIHW was not provided with further details of how sufficient total spending or outlier transaction patterns were determined.

The sample and weights were recalculated each week and when new data became available (for example, at the end of the month). The resulting sample population was typically 2 million customers.

Classification by establishment type

Raw data were processed to identify brands and stores based on free-text fields of data from terminals used to process payments. Data were then categorised into industry groups.

The main industry group of interest for the analyses in this report was dining. Transactions for the dining industry group were further classified into the following establishment types:

- cafe and restaurant
- major chain fast food and takeaway
- other fast food and takeaway.

The ‘cafe and restaurant’ category was based on the ANZSIC group ‘Cafes and Restaurants’, which includes services predominantly involved in providing food and beverages for consumption at the premises, where customers typically order and are served while seated, and then pay after eating (ABS 2013c).

The ‘major chain fast food and takeaway’ category included any transaction made at the following chains: Crust Pizza, Chicken Treat, Domino’s, Donut King, Eagle Boys Pizza, KFC, Hungry Jack’s, McCafe, McDonald’s, Nando’s, Noodle Box, Oporto, Pizza Capers, Pizza Haven, Pizza Hut, Red Rooster, Subway and Wendy’s. These chains were chosen as they have previously been used in analysis of access to major fast food outlets by the ABS (ABS 2019c).

The ‘other fast food and takeaway’ category was based on the ANZSIC group ‘Takeaway Food Services’, except for those already captured by the major chain fast food and takeaway category. The ANZSIC group ‘Takeaway Food Services’ includes services predominantly involved in providing food and beverages ready to be taken away for immediate consumption, usually in takeaway packaging, with customers paying before eating (ABS 2013c).

Pubs, taverns and bars were excluded from analysis of the dining group. As it is not possible to determine what was purchased using electronic payment data, it was not possible to differentiate between food and alcohol purchasing. While some of the other establishments included (such as cafes and restaurants) will include some alcohol purchasing, they are less likely to include purchases solely of alcohol than pubs, taverns and bars.

Classification by payment type

Transactions were classified as ‘delivery or app purchase’ or ‘in person’. Delivery or app purchase included any transaction not made in person (for example, over the phone, online or through an app).

Cash adjustment

As mentioned in ‘Chapter 4 Electronic payment data’, the proportion of overall payments (by number of payments) made with cash, cards and other methods has changed over time in Australia. From 2013 to 2016, the percentage of payments made with card increased from 43% to 52%, while those made with cash decreased from 47% to 37% (Doyle et al. 2017). This trend also occurred in the food retail category (which excludes supermarkets), where card payments increased from 27% to 43% and cash payments decreased from 72% to 55%. There has also been an increase in the use of cards for lower value payments—in 2013, 18% of $1–10 payments and 39% of $11–20 payments were made by card, compared with 32% and 52%, respectively, in 2016. There are also differences in the use of card and cash as payment methods by age, income and geographic location.

To minimise the effect of the shift from cash to card payments, and more accurately reflect total spending, an adjustment was applied to some spending measures to incorporate an estimate of cash payments into the spend amount.

Three major data sources were used in the cash adjustment:

- ABS Retail Trade data, which estimates turnover from the monthly Retail Business Survey (a survey of around 500 large businesses and around 2,700 smaller businesses)
- electronic payment data, which provides total weighted spend by industry group
- a calculated cash location adjustment factor, derived from electronic payment to cash relativities of retail spending by location.

Using these sources, industry-specific total cash spending was derived as the difference between the ABS Retail Trade data and the weighted transactional data for each industry. The cash spending was then attributed to the geographic areas used in these analyses, based on the cash location adjustment factor calculated for the area.

The cash adjustment was applied to measures of dining spending; however, in the analysis by payment type, it was not applied to delivery or app purchases. The cash adjustment was not applied to measures of transaction frequency or transaction value—these measures are based on electronic payments only.

Inflation

The data presented in these analyses are in nominal dollars. Inflation is present in the data as the data reflect real purchasing patterns. No factors have been incorporated to adjust for this effect.

Analysis by age group

Electronic payment data were analysed by the following age groups, based on the age of the customer at the time of transaction: 15–24, 25–34, 35–44, 45–54, 55–64 and 65 and over.

Analysis by socioeconomic area, remoteness area and Primary Health Network area

The electronic payment data contained the customer mailing address for each customer and so were also a source of location data.

Electronic payment data were analysed by socioeconomic area, remoteness area and PHN area, based on the customer mailing address. For the majority of customers, the SA1 the address was located in was available and used to group customers by socioeconomic areas, remoteness areas and PHN areas. Where SA1 data were not available, postal area data were used. The proportion of customers whose customer mailing address was in a different SA1 to their residential address was unknown, so the level of any misclassification of socioeconomic area, remoteness area and PHN area was also unknown.

A very small proportion of customers belonged to SA1s that were split across multiple PHNs. These customers were apportioned as per the ratio for each PHN.

Correlation with overweight and obesity

The PHN area data were compared with estimates of the prevalence of adult overweight and obesity by PHN area in 2017–18 and reviewed for correlations (AIHW 2019b).

General considerations for interpretation of electronic payment data

The following considerations apply to several of the example analyses presented in the following text and should be kept in mind when interpreting the data.

Data coverage

The raw data used in these analyses do not reflect all spending on dining out in Australia—they reflect only transactions made using electronic payment methods, and do not include cash payments. While adjustments have been made to some measures to include an estimate of cash spending, other measures reflect only transactions made using electronic payment methods.

While the data provide information about the value and frequency of transactions, they do not provide information about what was purchased, limiting conclusions about the quantities or nutritional quality of items purchased. As an example, it is not possible to distinguish purchasing of a non-discretionary food (such as coffee) from a discretionary food (such as potato chips).

Comparisons between areas and over time

Differences between population groups, between areas or over time may partly be influenced by differences in payment methods. The percentage of payments made using cards has increased over time, with the largest increase in the relative use of cards for lower-value transactions (Doyle et al. 2017). The percentage of payments made with cards is generally higher among younger individuals than older individuals and among households with higher incomes than among households with lower incomes.

Differences between areas may, in part, also reflect differences in what establishments are available between areas. Limited data related to this are published and what data are available may not be for the relevant time period.

However, as an example, a Victorian study, based on data sourced in 2013, found that there was no difference in either the presence of fast food restaurants (defined in this study as McDonald's, KFC, Hungry Jack's and Red Rooster) or the mean number of fast food restaurants between *Major cities*, *Inner regional* areas and *Outer regional* areas, after adjustments for population, geographic area and the percentage of the population aged less than 25 years (there were no *Remote* or *Very remote* areas in the study area) (Thornton et al. 2016). A higher proportion of the most disadvantaged areas had at least 1 fast food restaurant than the least disadvantaged areas. The most disadvantaged areas also had a higher mean number of fast food restaurants than the least disadvantaged areas.

While differences between areas may, in part, reflect differences in what establishments are available between areas, it should be noted that the analyses in this section were based on customer address, not the location of the establishment.

No adjustments related to inflation were made in these analyses.

Classification by establishment type

The establishment types (cafe and restaurant, major chain fast food and takeaway, and other fast food and takeaway) used in the analyses were based to some extent on ANZSIC groups, which were developed for use in compiling and analysing industry statistics. ANZSIC groups were not developed to consider the nutritional quality of foods available through food retail outlets. As such, there is likely to be large variation in the nutritional quality of foods available from outlets within the same establishment type.

Results based on establishment type could therefore differ based on how food retail outlets are grouped.

Comparisons with other data sources

Electronic payment data were compared with household expenditure data from the HES 2015–16. Noteworthy differences between the sources include that:

- HES data includes all sources of spending recorded by respondents including items paid for by cash, cheque and electronic payments

- the electronic payment data are at the cardholder level, while HES data are at the household level
- classifications may differ between sources.

Example analysis: Average monthly spend on dining out

The average amount of money people spend on dining out provides some indication of their level of eating out of home. Previous analyses have shown that eating out is associated with poorer nutritional intake and health outcomes, for example:

- the relative contribution of fat to energy intake was higher, and intakes of fibre and selected micronutrients were lower, among men and women who consumed a higher proportion of their energy intake from foods prepared outside the home (defined as foods sourced from restaurants, cafes, cafeterias and takeaway/pizza/fast food places) (Burns et al. 2002)
- the prevalence of moderate abdominal obesity was higher among men and women who ate takeaway food (defined as hot takeaway meals, such as pizza, burgers, fried or roast chicken, and Chinese/Indian/Thai takeaway) twice a week or more (Smith et al. 2009).

In this analysis, transaction data were analysed to measure the average monthly spend on dining out by establishment type and payment type, how this has changed over time, and how this differs between socioeconomic areas, remoteness areas, PHN areas and age groups.

The transaction data, weighted to the Australian population, were used as the numerator for this analysis, with the ABS Estimated Resident Population used as the denominator (therefore the average monthly spend on dining out is the average monthly spend on dining out per person in Australia). The average monthly spend on dining out has also been adjusted to incorporate an estimate of cash payments.

This analysis provides an example of how electronic payment data could be used for monitoring trends in food expenditure and comparing food expenditure by sociodemographic characteristics.

Some of the PHN area data were also compared with estimates of the prevalence of adult overweight and obesity by PHN area in 2017–18 (AIHW 2019b). This provides an example of how electronic payment data could be used to analyse associations between food expenditure and health outcomes.

Results

On average, customers spent a total of $148 per month on dining out in 2018. Over half of this was for cafes and restaurants ($86), followed by other fast food and takeaway ($34), and major chain fast food and takeaway ($28). Of the average $148 monthly spend on dining out, the majority was attributable to in person purchases ($138) rather than delivery or app purchases ($10).

The average monthly total spend on dining out increased slightly over time from $140 in 2015 to $148 in 2018. This was mostly driven by an increase in average monthly spend for other fast food and takeaway, from $22 to $34. The average monthly spend for cafes and restaurants decreased from $91 to $86. The amount attributable to in person purchases was similar over time ($137 in 2015 and $138 in 2018), while the amount attributable to delivery or app purchases increased from $3 in 2015 to $10 in 2018.

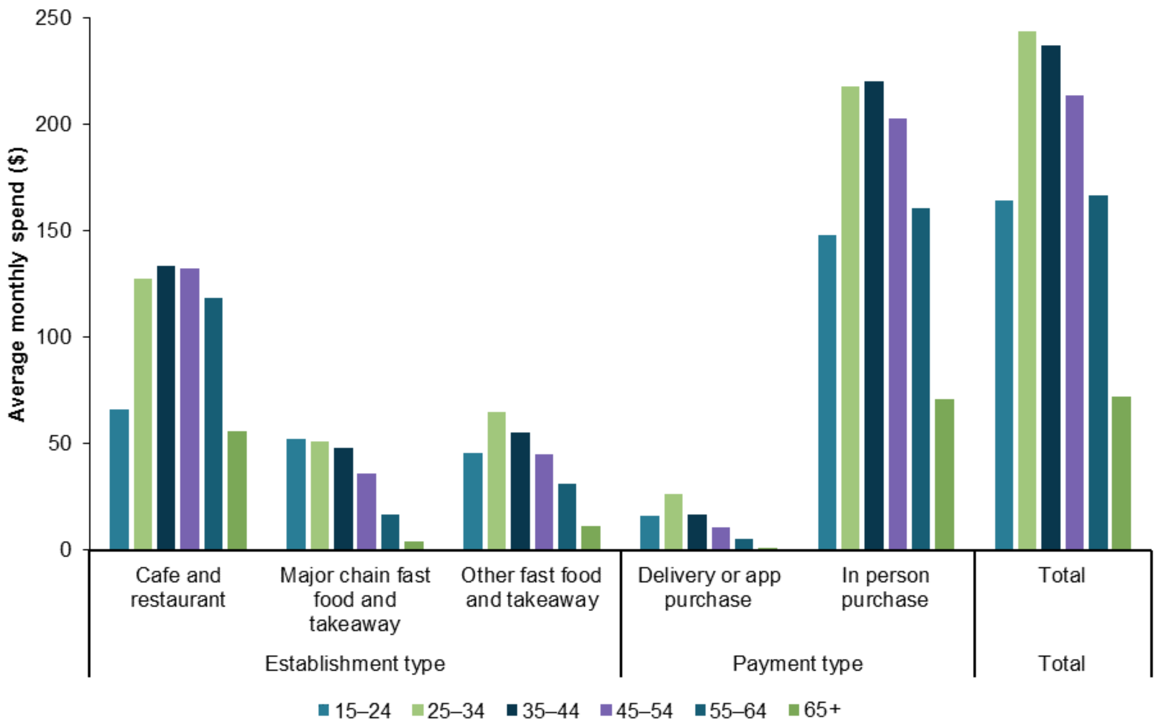
By age group, the average monthly total spend on dining out was highest for the 25–34 age group and lowest for the 65 and over age group (Figure 7.1). The patterns by age group differed for different establishment types—the average monthly spend for:

- cafes and restaurants was highest for the 35–44 and 45–54 age groups and lowest for the 65 and over age group
- major chain fast food and takeaway was highest for the 15–24 and 25–34 age groups and lowest for the 65 and over age group
- other fast food and takeaway was highest for the 25–34 age group and lowest for the 65 and over age group.

The average monthly spend for each establishment type can also be looked at as a proportion of the average monthly total spend on dining out. The proportion of the average monthly total spend on dining out spent at cafes and restaurants increased with age from 40% for the 15–24 age group to 78% for the 65 and over age group. In contrast, the proportion spent at major chains decreased with age from 32% for the 15–24 age group to 6% for the 65 and over age group.

Average monthly in person purchasing was highest for the 25–34 ($218) and 35–44 ($221) age groups, while average monthly delivery or app purchasing was highest for the 25–34 age group ($26) (Figure 7.1). The proportion of spend that was attributable to delivery or app purchasing ranged from 2% for the 65 and over age group to 11% for the 25–34 age group.

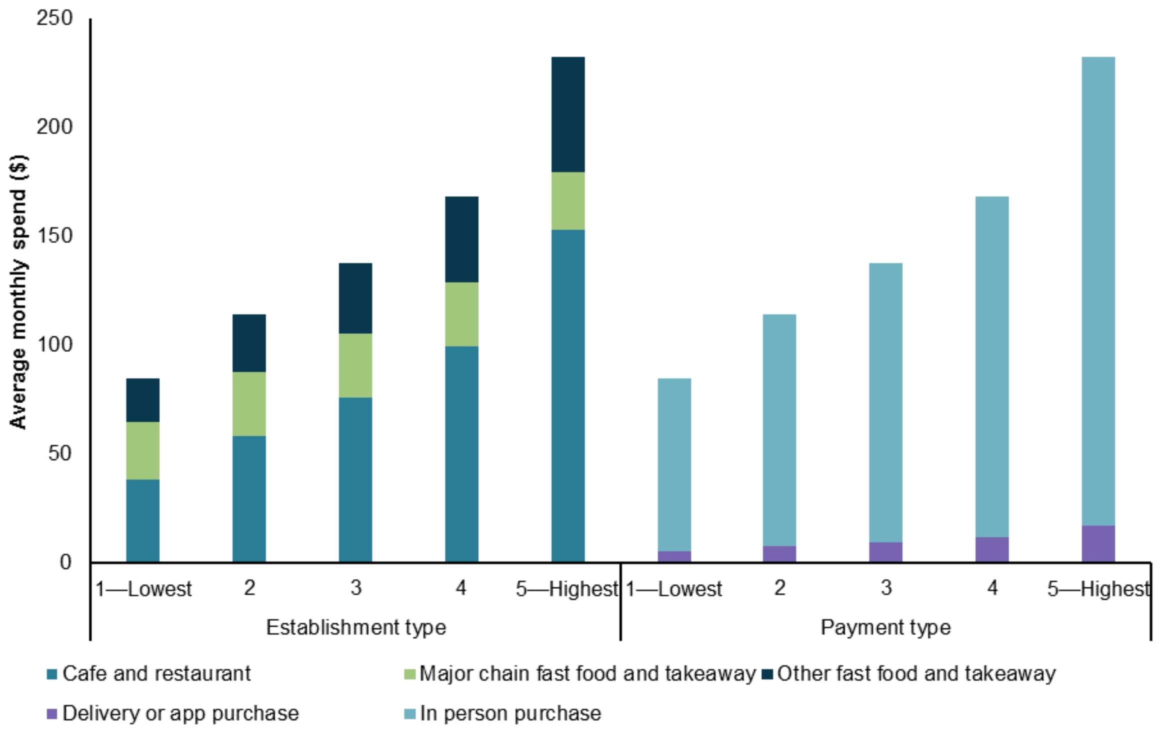
Figure 7.1: Average monthly spend on dining out, by age group, establishment type and payment type, 2018



Source: Data provider analysis of electronic payment data.

The average monthly total spend on dining out in 2018 for customers from the highest socioeconomic areas ($232) was 2.7 times as high as that for those from the lowest socioeconomic areas ($85) (Figure 7.2). Average monthly spend for cafes and restaurant, delivery, and other fast food and takeaway was higher for customers from the highest socioeconomic areas than for those from the lowest socioeconomic areas. However, for major chain fast food and takeaway, average monthly spend was similar across groups. The amounts attributable to both in person purchases and delivery or app purchases increased with increasing socioeconomic position.

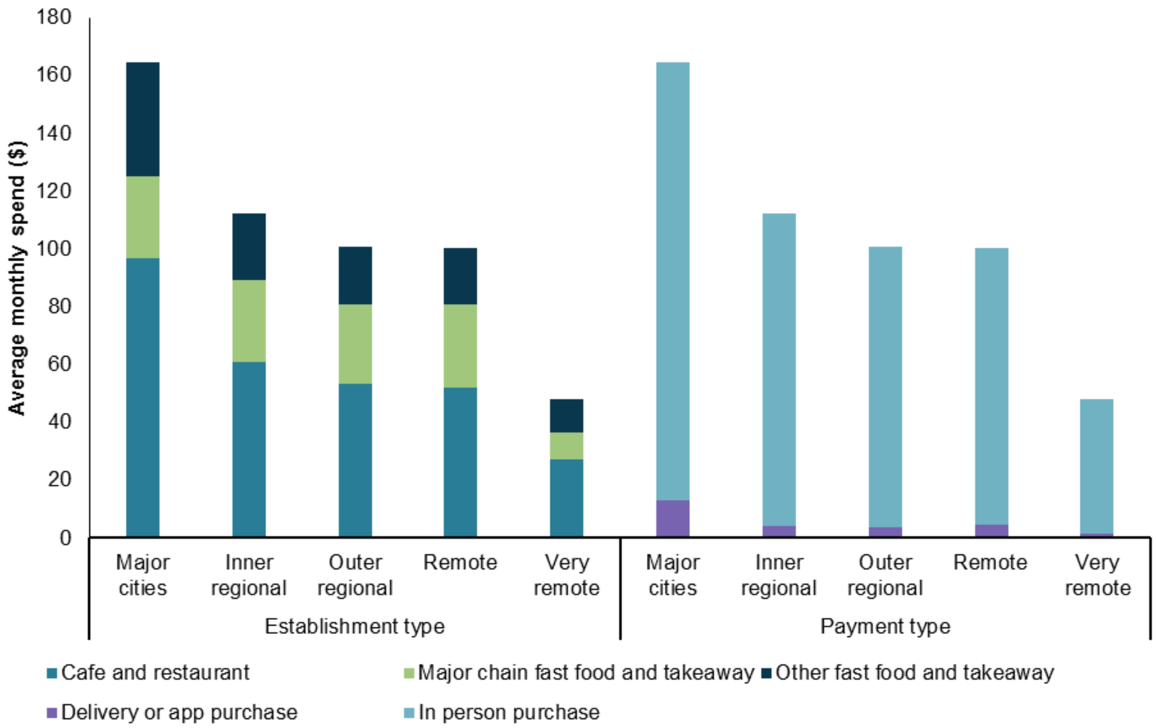
Figure 7.2: Average monthly spend on dining out, by socioeconomic group, establishment type and payment type, 2018



Source: Data provider analysis of electronic payment data.

The average monthly total spend on dining out was highest for customers from *Major cities* ($165) followed by *Inner regional* areas ($112), *Outer regional* areas ($101), *Remote* areas ($100) and *Very remote* areas ($48) (Figure 7.3). While average monthly spend for cafes and restaurants was higher for customers from *Major cities* than for those from other areas, the average monthly spend for major chain fast food and takeaway was similar across customers from *Major cities*, *Inner regional* areas, *Outer regional* areas and *Remote* areas but substantially lower in *Very remote* areas. The amount attributable to delivery or app purchases in *Major cities* was between 2.8 and 8.8 times as high as in other areas.

Figure 7.3: Average monthly spend on dining out, by remoteness area, establishment type and payment type, 2018



Source: Data provider analysis of electronic payment data.

The average monthly total spend on dining out varied widely between PHN areas (Figure A.1). The spends in the PHN areas with the highest average spends (which included Central and Eastern Sydney (NSW) ($216), Northern Sydney (NSW) ($215) and the Australian Capital Territory ($186)) were more than twice those of the PHN areas with the lowest (which included Western Queensland ($89), Country SA ($94) and Murrumbidgee (NSW) ($96)).

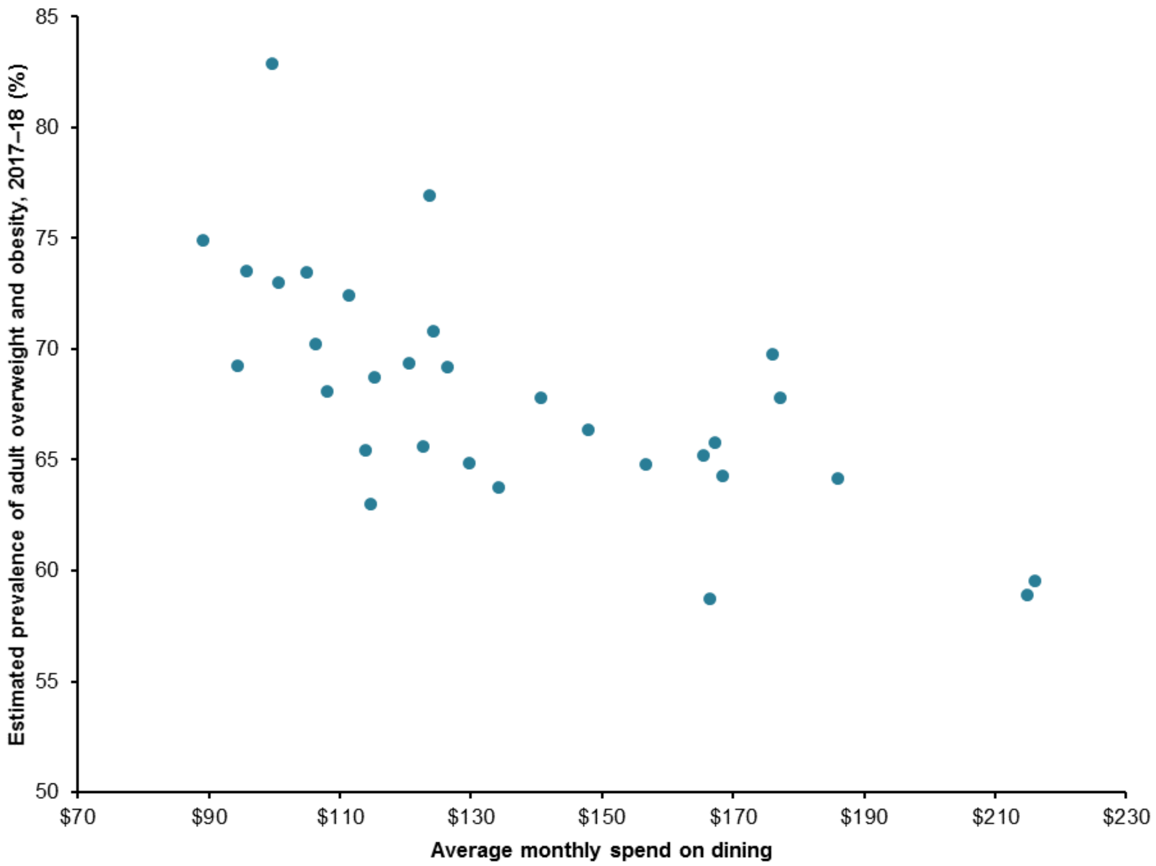
Although Central and Eastern Sydney (NSW) and Northern Sydney (NSW) had the highest average monthly total spend on dining out, they had the lowest average monthly major chain fast food and takeaway spends ($19 and $17, respectively). The average monthly major chain fast food and takeaway spend was highest for customers from Nepean Blue Mountains (NSW) ($39), Darling Downs and West Moreton (Qld) ($36) and Brisbane North (Qld) ($36).

The average monthly spend for in person purchases and delivery or app purchases also varied considerably by PHN area (Figure A.2), with the average monthly spend for:

- in person purchases highest in Northern Sydney (NSW) ($198), Central and Eastern Sydney (NSW) ($194) and the Australian Capital Territory ($172) and lowest in Western Queensland ($84), Country SA ($91) and Murrumbidgee (NSW) ($92)
- delivery or app purchases highest in Central and Eastern Sydney (NSW) ($22), Northern Sydney (NSW) ($17), North Western Melbourne (Vic) ($15) and Brisbane North (Qld) ($15) and lowest in Gippsland (Vic), North Coast (NSW) and Country SA (all $3).

By PHN area, there was a strong negative significant correlation between the prevalence of overweight and obesity (2017–18) and average monthly total spend on dining out (r_s = –0.70, $p < 0.001$) (Figure 7.4). That is, a higher prevalence of overweight and obesity was associated with lower average monthly total dining spend.

Figure 7.4: Estimated prevalence of adult overweight and obesity (2017–18) and average monthly total spend on dining out (2018), by Primary Health Network area



Source: AIHW analysis of electronic payment data and AIHW 2019b.

Interpretation

Based on the electronic payment data, the average monthly spend on dining out per customer was $140 in 2015. Comparison of this absolute amount to estimates from other data sources is difficult, given differences in the level of the estimate and differences in scope. For example, based on the HES 2015–16, the average household weekly expenditure on meals out and fast foods in 2015–16 was $80.43 (ABS 2017b), equating to around $350 per month. However, this estimate is at the household (rather than customer) level. There are also differences in scope and definitions between data sources.

Broad comparisons of trends or patterns by socioeconomic area, remoteness area and age group in the electronic payment data and other data sources are possible:

- Based on the electronic payment data, the average monthly total spend on dining out increased by 6% from 2015 to 2018 (from $140 to $148 per month). Published ABS Retail Trade data also show an increase, which is greater than the increase in population over the same period—cafe, restaurant and takeaway food services turnover increased by 12% from 2015 to 2018, or by 6.6% on a per capita basis (ABS 2019d, 2020a). As previously noted, the electronic payment data were not adjusted for inflation, which may have contributed to some of the changes.

- Based on the electronic payment data, the average monthly total spend on dining out in 2015 in the highest socioeconomic areas was 2.6 times as high as that in the lowest. Published HES 2015–16 results (which use household income, rather than area-level disadvantage to group households into socioeconomic groups) show similar patterns—the average household weekly expenditure on meals out and fast foods in 2015–16 for the fifth of households with the highest equivalised disposable income was 4.8 times as high as for those in the fifth of households with the adjusted lowest income (ABS 2017b).

Some of the differences between areas may in part reflect differences in availability or access—for example, the higher average monthly spend attributable to delivery or app purchases in *Major cities* compared with other areas.

By PHN area, as the prevalence of overweight and obesity in 2017–18 increased, the average monthly total spend on dining out for 2018 decreased. However, this relationship should be considered with caution as other factors, such as socioeconomic position, may be related to both total dining spend and overweight and obesity. As noted above, average household weekly expenditure on meals out and fast foods was higher in higher income households in the HES 2015–16 (ABS 2017b), while the prevalence of overweight and obesity among adults is lower in higher socioeconomic areas (AIHW 2019b).

It is also not possible to determine from the average monthly total spend on dining out the quantities purchased or nutritional quality of items purchased—as an example, it is not possible to distinguish purchasing of a non-discretionary food (such as coffee) from a discretionary food (such as potato chips). The same average monthly total spend on dining out could reflect vastly different amounts of kilojoules, for example, depending on what was purchased.

Average dining out spend was adjusted to include an estimate of cash spending, however, the AIHW was not provided with full details of this method. It is difficult to assess the impact of this estimate without access to these details or to the raw data.

Recommendation

The above comparisons suggest that electronic payment data could be used to complement more traditional data sources (such as the HES) for monitoring of broad patterns in food expenditure, such as trends or comparisons between sociodemographic groups. The data would not be at the same level as the HES but could still provide broad information.

For future analyses, alternate classifications for retailers could be considered. These include the Food Environment Score tool, an Australian tool that can be used to classify food outlets according to their healthiness (Moayyed et al. 2017a).

Example analysis: Average monthly dining out transaction frequency

The average frequency of transactions for dining out provides some indication of people's level of eating out of home.

Transaction data were analysed to measure the average number of dining out transactions per month by establishment type and payment type, how this has changed over time, and how this differs between socioeconomic groups, remoteness areas, PHN areas and age groups.

The data weighted to the Australian population were used as the numerator for this analysis, with the ABS Estimated Resident Population used as the denominator (therefore the average monthly dining out transaction frequency is the average monthly dining out transaction frequency per person in Australia).

Some of the PHN area data were also compared with estimates of the prevalence of adult overweight and obesity by PHN area in 2017–18 (AIHW 2019b). This provides an example of how electronic payment data could be used to analyse associations between food expenditure and health outcomes.

Results

On average, customers made 6.5 dining out transactions per month in 2018. Transactions for cafes and restaurants were the most frequent (an average of 2.9 transactions per month), followed by major chain fast food and takeaway (1.9), and other fast food and takeaway (1.7). Of the average 6.5 transactions per month, the vast majority were in person transactions (6.2 per month) rather than delivery or app transactions (0.3).

The average number of dining out transactions per month increased by 1.3 transactions from 2015 to 2018 (5.2 compared with 6.5). The largest absolute increase was for cafe and restaurant transactions, with an average additional 0.6 transactions per month in 2018 compared with 2015. The average number of in person transactions and delivery or app transactions both increased from 2015 to 2018—from 5.2 to 6.5 per month for in person transactions and from 0.06 to 0.3 per month for delivery or app transactions.

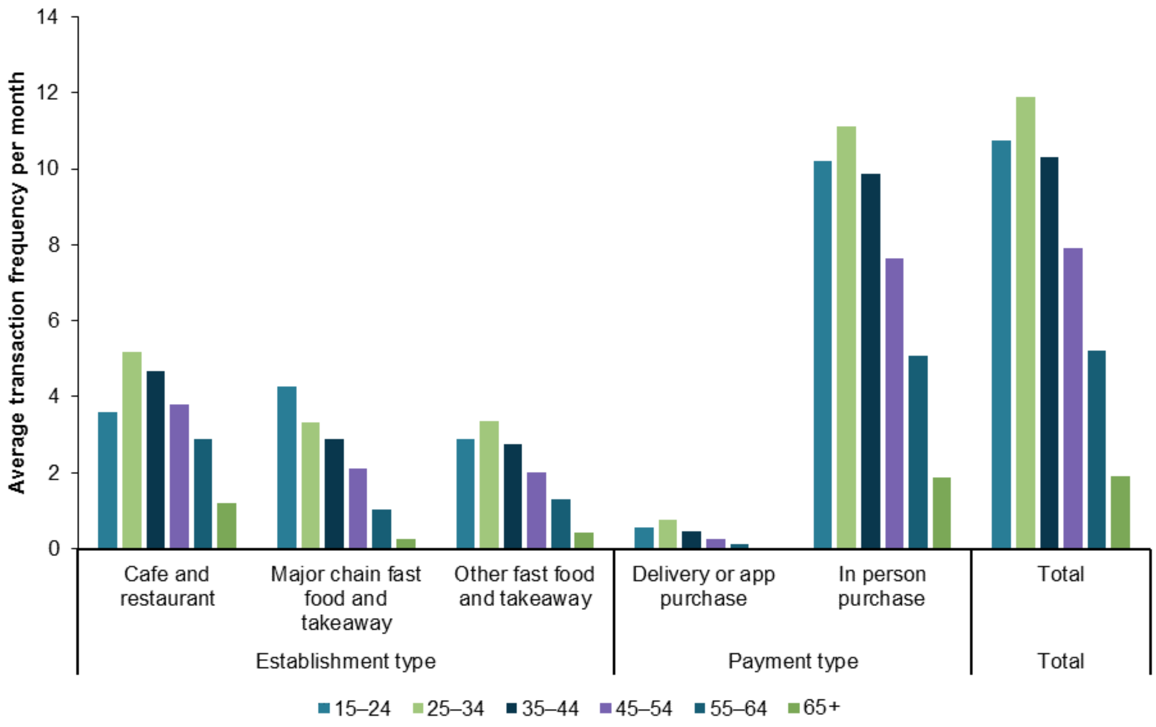
By age group, the average monthly dining out transaction frequency was highest for the 25–34 age group and lowest for the 65 and over age group (Figure 7.5). The patterns by age group differed for different establishment types—the average monthly transaction frequency for:

- cafes and restaurants was highest for the 25–34 age group and lowest for the 65 and over age group
- major chain fast food and takeaway was highest for the 15–24 age group and lowest for the 65 and over age group
- other fast food and takeaway was highest for the 25–34 age group and lowest for the 65 and over age group.

The average monthly transaction frequency for each establishment type can also be looked at as a proportion of the average monthly total dining out transaction frequency. The proportion of average monthly dining transactions made at cafes and restaurants increased with age from 33% for the 15–24 age group to 64% for the 65 and over age group. In contrast, the proportion made at major chains decreased with age from 40% for the 15–24 age group to 14% for the 65 and over age group.

Both average monthly in person transactions and delivery or app transactions were highest for the 25–34 age group (11.1 and 0.8 per month, respectively) (Figure 7.5). Although the proportion of transactions that were delivery or app transactions was low across all age groups, it ranged from 1% for the 65 and over age group to 6% for the 25–34 age group.

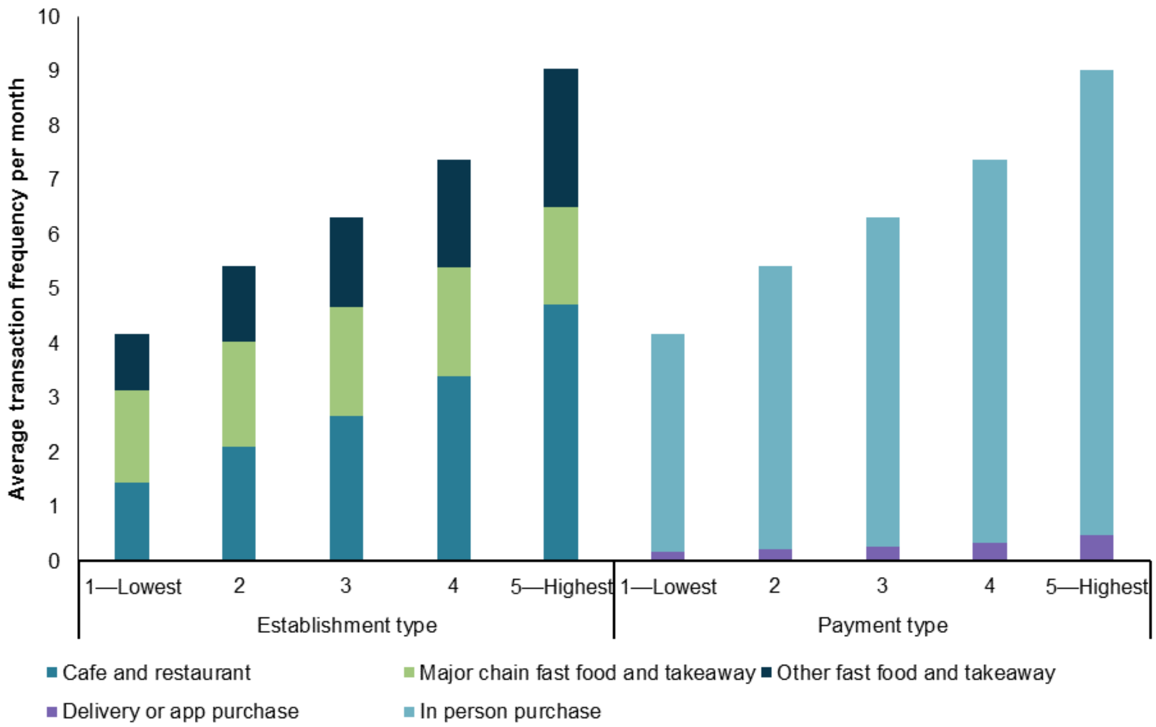
Figure 7.5: Average monthly dining out transaction frequency, by age group, establishment type and payment type, 2018



Source: Data provider analysis of electronic payment data.

In 2018, the average number of dining out transactions per month for customers from the highest socioeconomic areas (9.0) was more than twice that for those from the lowest socioeconomic areas (4.2) (Figure 7.6). The average number of transactions per month for cafes and restaurants, delivery and other fast food and takeaway also followed this pattern. However, the average number of transactions per month for major chain fast food and takeaway was similar across socioeconomic areas. The average number of transactions per month for both in person transactions and delivery or app transactions was highest for customers from the highest socioeconomic areas and lowest for those from the lowest socioeconomic areas.

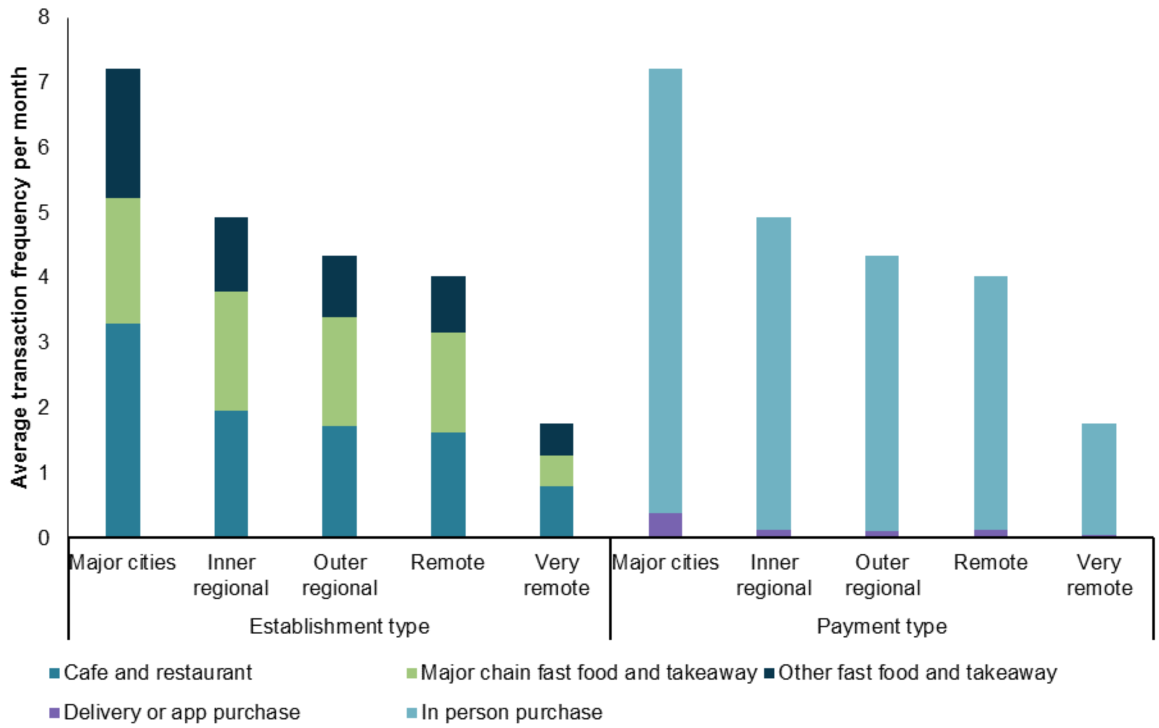
Figure 7.6: Average monthly dining out transaction frequency, by socioeconomic group, establishment type and payment type, 2018



Source: Data provider analysis of electronic payment data.

The average number of dining out transactions per month was highest for customers from *Major cities* (7.2), followed by *Inner regional* areas (4.9), *Outer regional* areas (4.3), *Remote* areas (4.0) and *Very remote* areas (1.8) (Figure 7.7). This pattern was similar for cafe and restaurant and other fast food and takeaway transactions. The average number of major chain fast food and takeaway transactions per month was also similar across customers from *Major cities* (1.9), *Inner regional* areas (1.8), *Outer regional* areas (1.7) and *Remote* areas (1.5) and lower for customers from *Very remote* areas (0.5). The average number of in person transactions per month was highest in *Major cities* and lowest in *Very remote* areas. The average number of delivery or app purchases per month in *Major cities* was between 3.1 and 9.6 times as high as in other areas.

Figure 7.7: Average monthly dining out transaction frequency, by remoteness area, establishment type and payment type, 2018



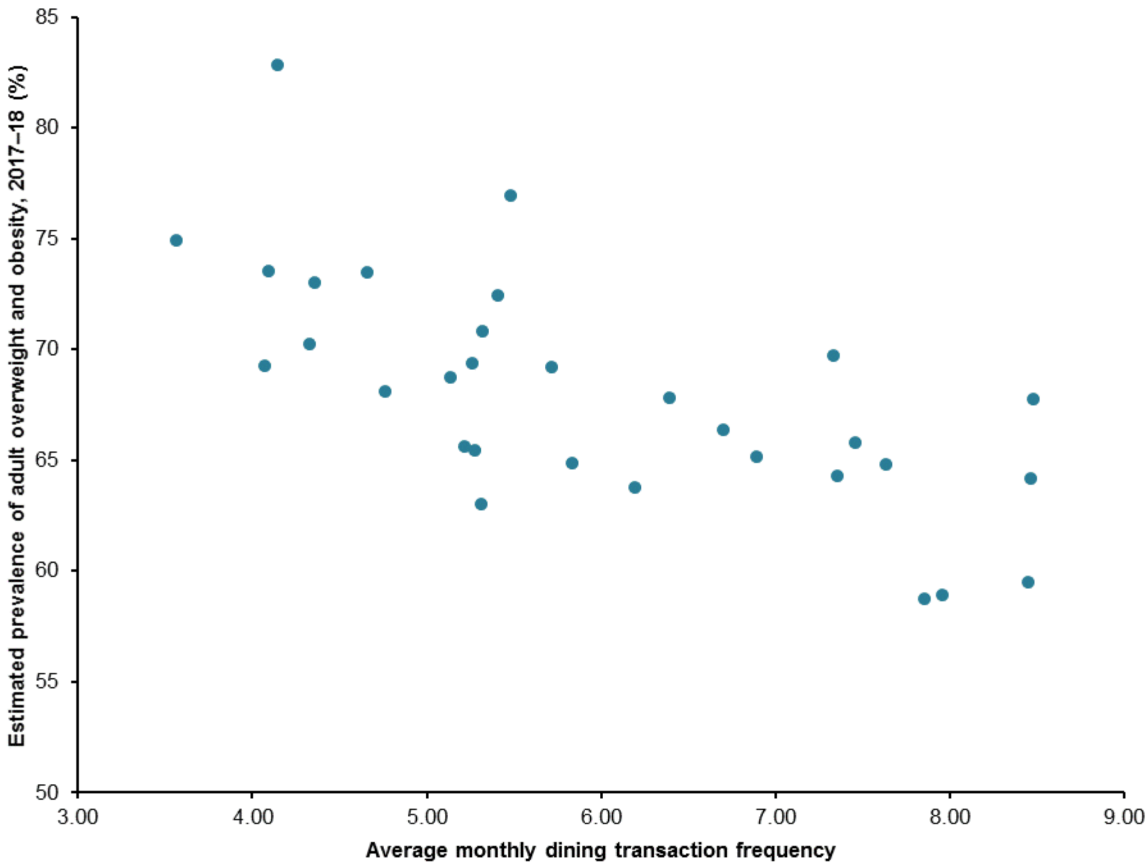
Source: Data provider analysis of electronic payment data.

There was large variation in the average number of dining out transactions per month by PHN area (Figure A.3). The average for customers from Brisbane North (Qld), Australian Capital Territory and Central and Eastern Sydney (NSW) (8.5) was more than twice that for customers from Western Queensland (3.6), Country SA, Murrumbidgee (NSW) and Western NSW (all 4.1).

The average number of in person transactions per month was highest for the Australian Capital Territory (8.1), Brisbane North (Qld) (8.1) and Central and Eastern Sydney (NSW) (7.8) and lowest for Western Queensland (3.4), Country SA (4.0), Murrumbidgee (NSW) (4.0) and Western NSW (4.0) (Figure A.4). The average number of delivery or app purchases per month was highest for Central and Eastern Sydney (NSW) (0.7) and Northern Sydney (NSW) (0.5)—10 PHN areas had the lowest value (0.1).

There was a moderate-strong negative significant correlation between the prevalence of overweight and obesity in 2017–18 and average monthly dining out transaction frequency in 2018 (r = –0.69, p < 0.001) by PHN area (Figure 7.8). That is, as the prevalence of overweight and obesity increased, the average number of monthly dining out transactions decreased.

Figure 7.8: Estimated prevalence of adult overweight and obesity (2017–18) and average monthly dining out transaction frequency (2018), by Primary Health Network area



Source: AIHW analysis of electronic payment data and AIHW 2019b.

Interpretation

The average monthly dining out transaction frequency is based on electronic payments only and does not include cash payments. As such, interpretation of trends in average monthly dining out transaction frequency and differences between sociodemographic groups is difficult due to changes over time and differences between groups in the use of electronic payment methods.

Some of the 25% increase in the average number of dining out transactions per month from 5.2 in 2015 to 6.5 in 2018 may reflect a potential increase in use of electronic payment methods, rather than an increase in the frequency of eating out. Although the time periods are not directly comparable, the proportion of all payments made by card increased by 21% from 2013 to 2016 (Doyle et al. 2017).

Similarly, customers from the highest socioeconomic areas had 1.8 times as many dining out transactions per month in 2016 compared with those from the lowest. However, according to the Reserve Bank of Australia, people in the highest household income group made a higher percentage of payments using card than those in the lowest (Doyle et al. 2017).

Conclusions drawn from data within a sociodemographic group (rather than between sociodemographic groups) may be more valid, although may still be influenced by differences in use of payment methods for different payment values. A lower percentage of lower value payments are made with card than that for higher value payments (Doyle et al. 2017).

In addition, although it provides information about the frequency of dining out, the average monthly dining out transaction frequency does not provide any information about quantities purchased or consumed or the nutritional quality of purchases—it is possible that some sociodemographic groups may be more frequent purchasers, but consume smaller quantities or items of differing nutritional quality. As the prevalence of overweight and obesity in 2017–18 increased, the average number of monthly dining out transactions for 2018 decreased across PHN areas. However, this relationship should be considered with caution as other factors, such as remoteness areas may be related to both monthly dining transaction frequency and overweight and obesity. For example, average monthly dining out transaction frequency was higher in *Major cities*, which also have a lower prevalence of overweight and obesity among adults (AIHW 2019b).

Recommendation

Without complementary data on payment methods, electronic payment data related to average transaction frequency are difficult to interpret. If electronic payment methods are more widely and equally adopted in the future, the data may become more useful as a proxy measure for eating outside of the home.

If this does occur, alternate classifications for retailers could be considered. These include the Food Environment Score tool, an Australian tool that can be used to classify food outlets according to their healthiness (Moayyed et al. 2017a).

Example analysis: Average dining out transaction value

As with dining out spend and dining out transaction frequency, the average value of transactions for dining out provides some indication of people's level of eating out of home.

In this analysis, transaction data were analysed to measure the average dining out transaction value (in $) by establishment type and payment type, how this has changed over time, and how this differs between socioeconomic groups, remoteness areas, PHN areas and age groups.

Some of the PHN area data were also compared with estimates of the prevalence of adult overweight and obesity by PHN area in 2017–18 (AIHW 2019b). This provides an example of how electronic payment data could be used to analyse associations between food expenditure and health outcomes.

Results

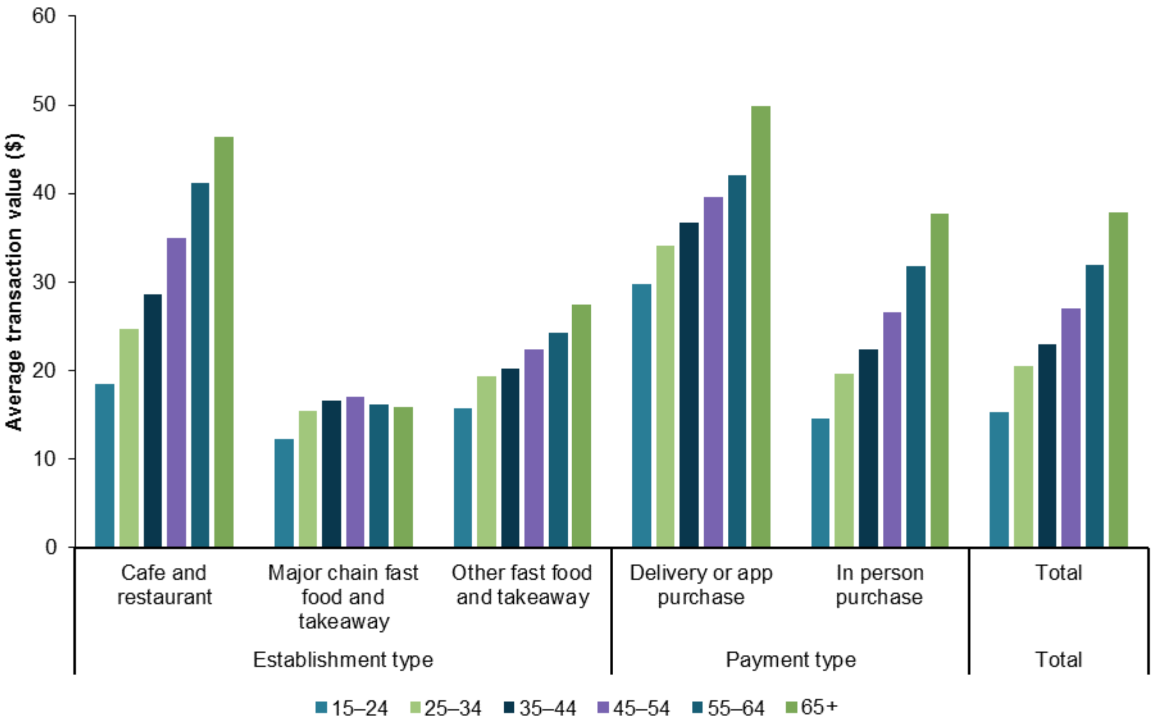
The average transaction value for dining out was $23 in 2018. The average transaction value ranged from $30 for cafes and restaurants to $20 for other fast food and takeaway and $15 for major chain fast food and takeaway. The average transaction value for delivery or app purchases ($35) was higher than that for in person purchases ($22).

The average transaction value for dining out decreased from $27 in 2015 to $23 in 2018. This was driven by a decrease in the average transaction value for cafes and restaurants (from $40 in 2015 to $30 in 2018). The average transaction value remained similar over time for major chain fast food and takeaway ($15 in both 2015 and 2018) and other fast food and takeaway ($20 in both 2015 and 2018). The average transaction values for in person purchases and delivery or app purchases both decreased from 2015 to 2018—from $27 to $22 for in person purchases and from $40 to $35 for delivery or app purchases.

By age group, the average dining out transaction value was highest for the 65 and over age group and lowest for the 15–24 age group (Figure 7.9). For cafes and restaurants and other fast food and takeaway, the average transaction value followed the same pattern. For major chain fast food and takeaway, the average transaction value was highest for the 45–54 age group and lowest for the 15–24 age group (Figure 7.9).

The average transaction values for both in person purchases and delivery or app purchases increased with age (Figure 7.9).

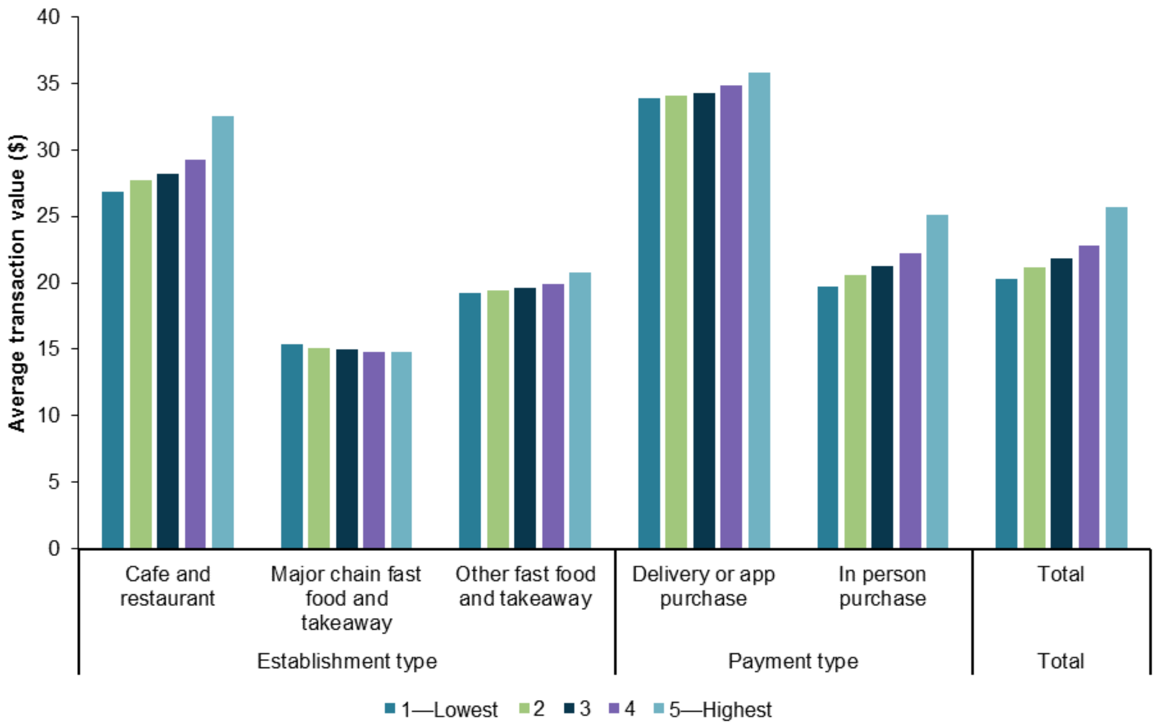
Figure 7.9: Average dining out transaction value, by age group, establishment type and payment type, 2018



Source: Data provider analysis of electronic payment data.

The average transaction value for dining out in 2018 was highest for customers living in the highest socioeconomic areas ($26) and lowest for those living in the lowest socioeconomic areas ($20) (Figure 7.10). This was largely due to a higher average transaction value for cafes and restaurants for customers from higher socioeconomic areas than for those from lower socioeconomic areas. The average transaction values for major chain fast food and takeaway and other fast food and takeaway were more similar across socioeconomic groups. The average transaction values for both in person purchases and delivery or app purchases increased with increasing socioeconomic position.

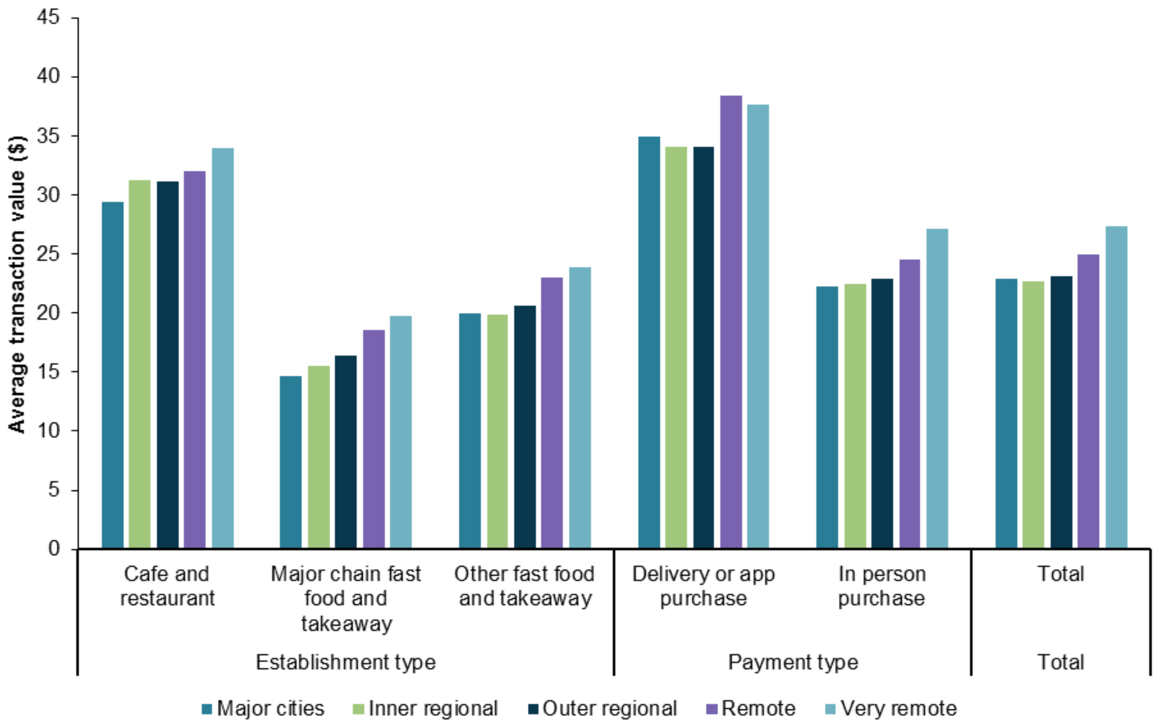
Figure 7.10: Average dining out transaction value, by socioeconomic group, establishment type and payment type, 2018



Source: Data provider analysis of electronic payment data.

The average transaction value for dining out in 2018 was slightly higher for customers from *Very remote* areas ($27) than for those from other areas ($23 for *Major cities*, *Inner regional* areas and *Outer regional* areas and $25 for *Remote* areas) (Figure 7.11). The average transaction value for in person purchases increased with increasing remoteness—the pattern for delivery or app purchases was less consistent.

Figure 7.11: Average dining out transaction value, by remoteness area, establishment type and payment type, 2018



Source: Data provider analysis of electronic payment data.

By PHN area (Figure A.5), the average transaction value for dining out was:

- highest for customers from Northern Sydney (NSW) ($27), Central and Eastern Sydney (NSW) ($26), Western Queensland ($25) and Country WA ($25)
- lowest for customers from Brisbane South (Qld) ($21), Darling Downs and West Moreton (Qld) ($21), Brisbane North (Qld) ($21) and Gold Coast (Qld).

There was no clear association between the prevalence of overweight and obesity in 2017–18 and average dining transaction value in 2018 across PHN areas (r = 0.04, p = 0.846).

Interpretation

The average transaction value for dining out is based on electronic payments only and does not include cash payments. As such, interpretation of trends in average transaction value for dining and differences between sociodemographic groups is difficult due to changes over time and differences between groups in the use of electronic payment methods.

The average transaction value does not provide any information about quantities purchased or consumed or the nutritional quality of purchases. The same average transaction value could reflect vastly different amounts of kilojoules, for example, depending on what was purchased.

As an example, the average transaction value for dining out decreased from $27 in 2015 to $23 in 2018. This may have been affected by the increasing use of cards for smaller payment values. According to the Reserve Bank of Australia, 32% of $1–10 payments and 52% of $11–20 payments were made by card in 2016 compared with 18% and 39%, respectively, in 2013 (Doyle et al. 2017).

Recommendation

Without complementary data on payment methods, electronic payment data related to average transaction value are difficult to interpret. If electronic payment methods are more widely and equally adopted in the future, the data may become more useful as a proxy measure for eating outside of the home.

If this does occur, alternate classifications for retailers could be considered. These include the Food Environment Score tool, an Australian tool that can be used to classify food outlets according to their healthiness (Moayyed Hamid et al. 2017a).

Example analysis 2b: Electronic payment data

This section of the report includes references to data provided by 1 of the largest 4 banks in Australia (based on share of assets held on banks' domestic books) on an anonymised and aggregated basis. The data provider did not author this report, nor is it intended to be an investment research report or relied upon in any way for making any investment decisions. No representation or warranty is made as to the accuracy or completeness of the data and it may not reflect all trends in the market. Rather, it is published solely for informational purposes.

The analyses of electronic payment data in this section were completed by the data provider. The AIHW completed the correlation analysis of electronic payment and overweight and obesity data.

General methods

Data source

Data for bank customers who made a card payment in person at a fast food merchant were included in the data source, giving a total sample size of approximately 6.5 million customers. Cash payments, online payments and payments made via food ordering apps were not included in the analysis. The data were aggregated and anonymised at the SA3 and PHN geographical area level and were for personal accounts only (that is, no business accounts). Data from April 2018 – March 2019 were used for this report.

Classification into industry groups

For this analysis, fast food transactions were restricted to those from merchants whose merchant category code included 'Fast-food/Takeaway' (5814) and ANZSIC code included 'Takeaway Food Services' (4512). The data were then filtered manually to remove any irrelevant merchants that may have been captured in these merchant category code and ANZSIC categories.

Analysis by Primary Health Network area and Statistical Area Level 3 region

Electronic payment data were analysed by PHN area and SA3 region based on the residential customer address.

There are 31 PHN areas and 358 SA3 regions across Australia. For each measure, the national and PHN area results are presented. As a demonstration of the variation in results by SA3 within the same PHN area, the results for the SA3s within 1 PHN area—Central and Eastern Sydney (NSW)—are included. Central and Eastern Sydney (NSW) was selected for this as 100% of the population of the PHN area lives in *Major citie*s, reducing the likelihood that observed differences were due to differences in remoteness. The results for this PHN area may not be representative of all PHN areas.

SA3 region results are also used in the correlation analyses (described below).

Correlation with overweight and obesity

The AIHW compared SA3 data with modelled estimates of the prevalence of adult overweight and obesity by SA3 in 2017–18 (PHIDU 2020) and reviewed for correlations.

For this section, the majority of the data were not normally distributed so to simplify comparisons and reporting results, Spearman's Rank correlations were used for all analyses.

General considerations for interpretation of electronic payment data

The following considerations apply to several of the example analyses presented in the following text and should be kept in mind when interpreting the data and subsequent results.

Data coverage

The data used in these analyses do not reflect all fast food spending in Australia—they reflect only transactions made by customers of the bank using card payments in person, so exclude cash payments, online payments and payments made via food ordering apps.

While there has been a shift away from cash payments to other methods, cash was still used for just over half (55%) of purchases from food retailers (which include specialty food stores, cafes, pubs and takeaway food outlets) in 2016 (Doyle et al. 2017). This was a decline from 72% in 2013.

While the data provide information about the spend and frequency of transactions, they do not provide information about what was purchased or how many people the purchase was for. This limits what conclusions can be drawn about the quantities or nutritional quality of items purchased.

The electronic payment data from the bank have not been weighted to the Australian population to correct for biases in market share.

Comparisons between areas

Differences between areas may partly be influenced by differences in payment methods. The percentage of payments made with cards is generally higher among younger individuals than older individuals and among households with higher incomes than among households with lower incomes (Doyle et al. 2017).

Differences between areas may also, in part, reflect differences in the composition of households of cardholders. It may also reflect differences in what establishments are available between areas. Limited data related to this are published and what data are available may not be for the relevant time period.

However, as an example, a Victorian study, based on data sourced in 2013, found that there was no difference in either the presence of fast food restaurants (defined in this study as McDonald's, KFC, Hungry Jack's and Red Rooster) or the mean number of fast food restaurants between *Major cities*, *Inner regional* areas and *Outer regional* areas, after adjustments for population, geographic area and the percentage of the population aged less than 25 years (there were no *Remote* or *Very remote* areas in the study area) (Thornton et al. 2016). However, a higher proportion of the most disadvantaged areas had at least 1 fast food restaurant when compared with the least disadvantaged areas. The most disadvantaged areas also had a higher mean number of fast food restaurants than the least disadvantaged areas.

While differences between areas may, in part, reflect differences in what establishments are available between areas, it should be noted that the analyses in this section were based on the geographic location of the customer (SA3), and not the geographic location of the establishment.

Classifications of food establishments

The classification of transactions in these example analyses was based on merchant category codes and ANZSIC codes. ANZSIC codes were developed for use in compiling and analysing industry statistics and do not consider the nutritional quality of foods available through food retail outlets. As such, there is likely to be vast variation in the nutritional quality of foods available from establishments of the same code.

There is, however, no consensus public health definition for what is considered 'fast food' or 'takeaway food'. The results in this chapter could differ based on how food establishments are classified.

Example analysis: Average annual fast food spend

The average amount of money people spend on fast food provides some indication of their level of eating out of home. Previous analyses have shown that eating out is associated with poorer nutritional intake and health outcomes, for example:

- the relative contribution of fat to energy intake was higher, and intakes of fibre and selected micronutrients were lower, among men and women who consumed a higher proportion of their energy intake from foods prepared outside the home (defined as foods sourced from restaurants, cafes, cafeterias and takeaway/pizza/fast food places) (Burns et al. 2002)
- the prevalence of moderate abdominal obesity was higher among men and women who ate takeaway food (defined as hot takeaway meals, such as pizza, burgers, fried or roast chicken, and Chinese/Indian/Thai takeaway) twice a week or more (Smith et al. 2009).

In this analysis, electronic payment data were analysed to measure the average annual fast food spend and how this differs between PHN areas and SA3s. Only those customers of the bank who made a fast food transaction during the reference period were included.

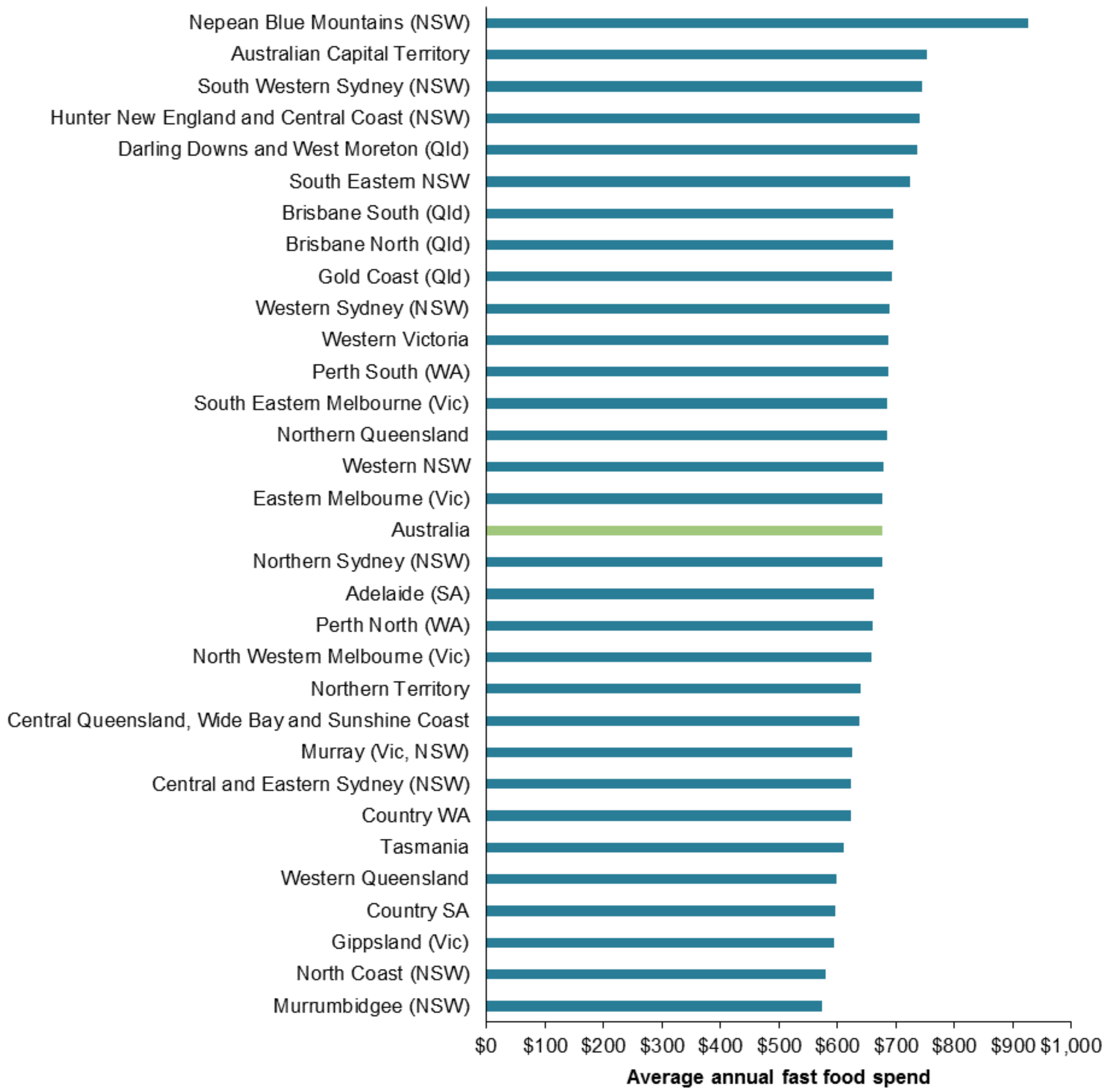
This analysis provides an example of how electronic payment data could be used for comparing food expenditure by sociodemographic characteristics.

The AIHW compared SA3 data with modelled estimates of the prevalence of adult overweight and obesity by SA3 in 2017–18 (PHIDU 2020). This provides an example of how electronic payment data could be used to analyse associations between food expenditure and health outcomes.

Results

The average annual fast food spend was $677 per customer (Figure 7.12). The average annual fast food spend varied substantially by PHN area—the highest average spend was $927 per year by customers from Nepean Blue Mountains (NSW), while the lowest was $573 per year by customers from Murrumbidgee (NSW).

Figure 7.12: Average annual fast food spend, by Primary Health Network area, April 2018–March 2019

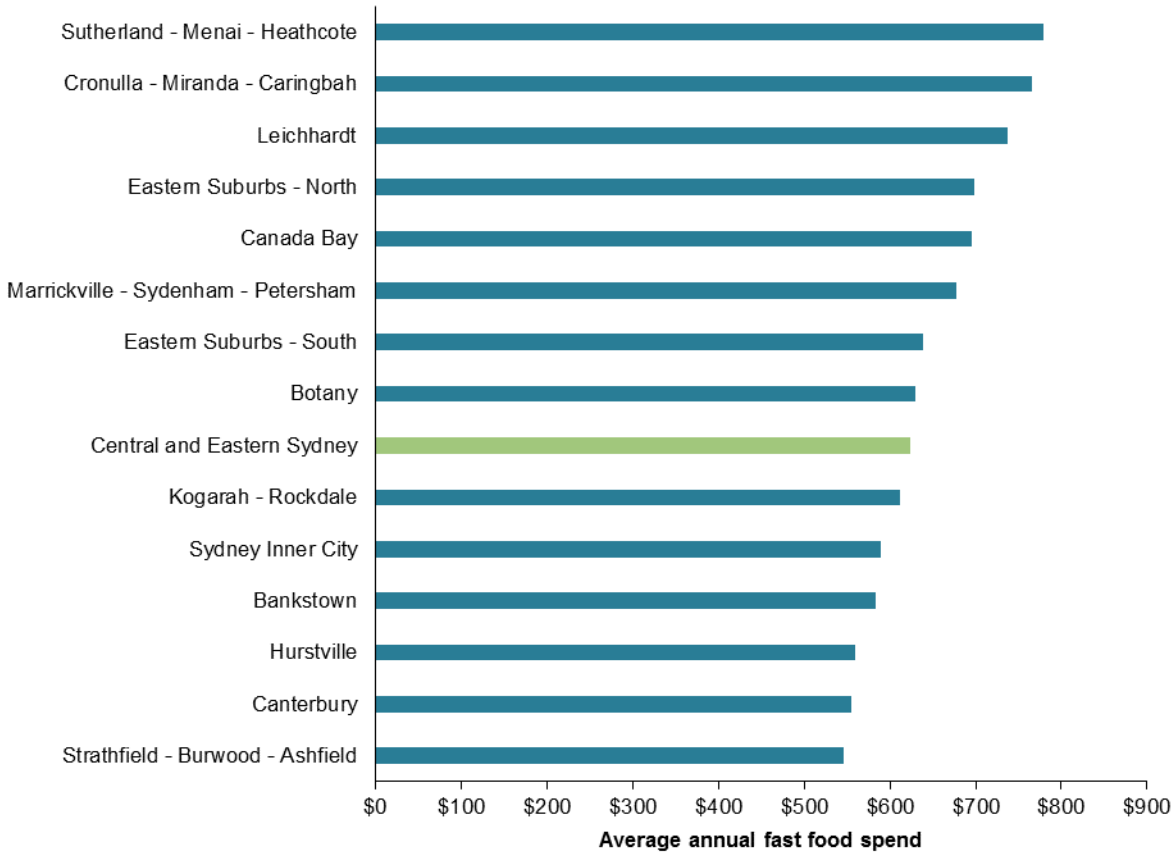


Source: Aggregated electronic payment bank data (April 2018 – March 2019).

Within PHN areas, the average annual fast food spend varied. Using the Central and Eastern Sydney (NSW) PHN area an example, the average annual fast food spend within the PHN area was $624 per customer. Of the SA3s within the PHN area that are part of mainland Australia (as this PHN area includes the Lord Howe Island and Norfolk Island SA3s), the average annual fast food spend varied from $546 per customer in Strathfield - Burwood - Ashfield to $779 per customer in Sutherland - Menai - Heathcote (Figure 7.13).

In the Central and Eastern Sydney (NSW) PHN area, the SA3s with higher average annual fast food spends generally contained more higher socioeconomic areas (based on SA1) and those with lower average annual fast food spends contained more lower socioeconomic areas (ABS 2018a). The results for this PHN area may not be representative of all PHN areas and results may differ depending on the socioeconomic profile of each individual SA3 region.

Figure 7.13: Average annual fast food spend, by Statistical Areas Level 3, Central and Eastern Sydney Primary Health Network area, April 2018 – March 2019



Source: Aggregated electronic payment bank data (April 2018 – March 2019).

There was no clear association between average annual fast food spend per customer from April 2018 – March 2019 and the prevalence of adult overweight and obesity in 2017–18 by SA3 (r_s = 0.10, p = 0.082).

Interpretation

The average annual fast food spend is based on card payments made in person and does not include cash payments, online payments or payments made via food ordering apps. As such, interpretation of differences in average annual fast food spend between sociodemographic groups is difficult due to differences between groups in the use of electronic payment methods.

Although there appears to be a pattern in the SA3 analysis of the Central and Eastern Sydney (NSW) PHN area towards higher average annual fast food spend in higher socioeconomic areas, this may in part be due to differences in payment methods. It could also reflect other factors, which may be related to average annual fast food spend, such as household composition.

However, data from the HES 2015–16 also show higher expenditure for fast food and takeaway (which excludes coffee and frozen foods) for higher socioeconomic groups—weekly expenditure in the highest household income group was more than 3 times as high as that in adjusted lowest household income group ($45.38 compared with $14.47, respectively).

The analysis may have been affected by some of the other limitations of electronic payment data, such as an inability to determine the items purchased or their quantities or nutritional quality—as an example, it is not possible to distinguish purchasing of a non-discretionary food (such as coffee) from a discretionary food (such as potato chips). Similarly, there is no consensus public health definition as to what is considered ‘fast food’ and different results may occur if a different definition was used and different retailers included.

The results may also be affected by factors not considered in the analysis, such as income or education level. Different results may have been seen if a different outcome (such as prevalence of overweight or obesity alone, or prevalence of abdominal overweight or obesity) were used.

Recommendation

Without complementary data on payment methods or household composition, electronic payment data related to average annual fast food spend are difficult to interpret. If electronic payment methods are more widely and equally adopted in the future, the data may become more useful as a proxy measure for eating outside of the home.

If this does occur, alternate classifications for retailers could be considered. These include the Food Environment Score tool, an Australian tool that can be used to classify food outlets according to their healthiness (Moayyed et al. 2017a).

Example analysis: Average annual fast food transaction frequency

As with average annual fast food spend, the average frequency of transactions for fast food provides some indication of people’s level of eating out of home.

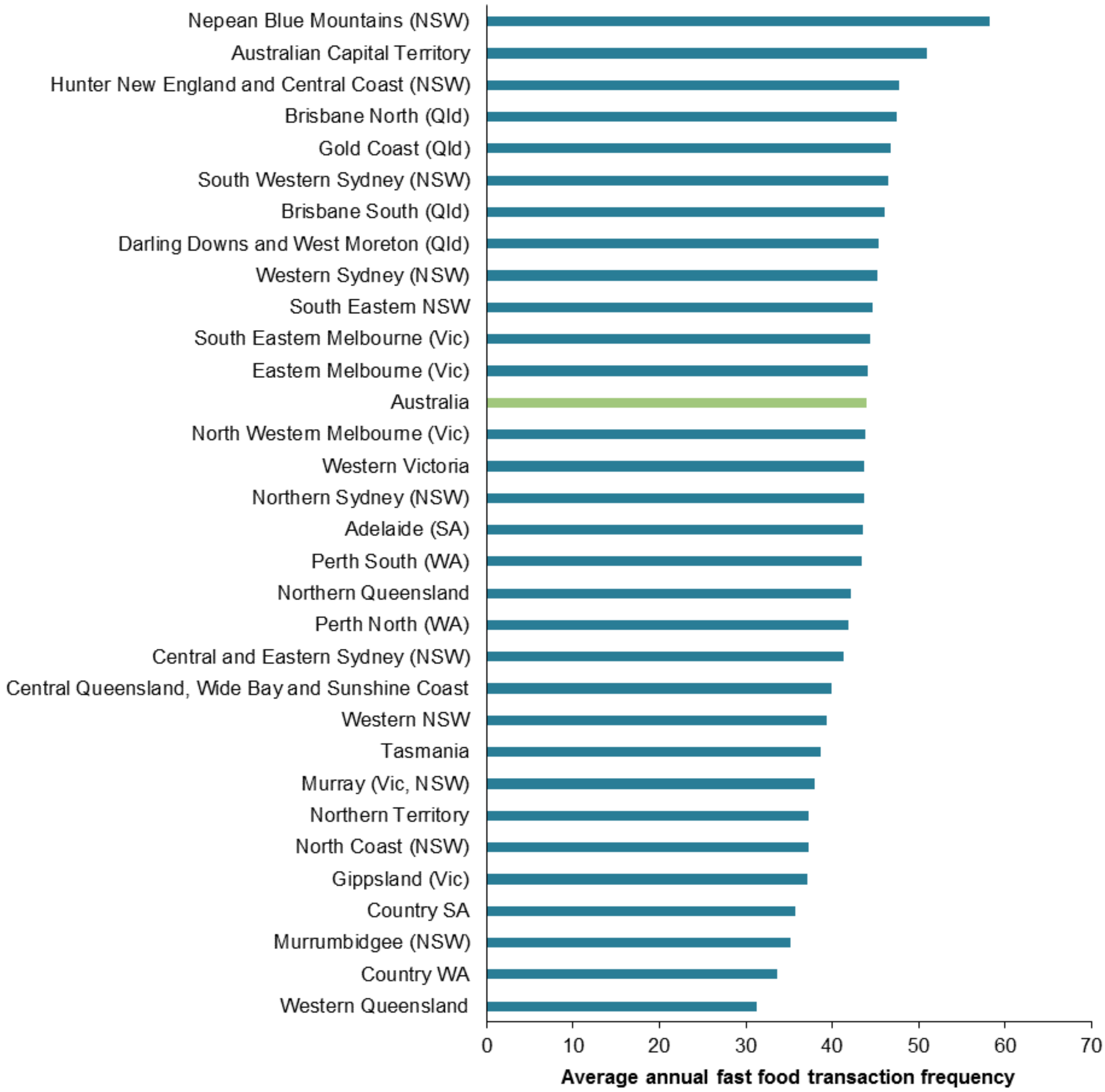
In this analysis, electronic payment data were analysed to measure the average number of fast food transactions per year and how this differs between PHN areas and SA3s. Only those customers of the bank who made a fast food transaction during the reference period were included.

The AIHW compared SA3 data with modelled estimates of the prevalence of adult overweight and obesity by SA3 in 2017–18 (PHIDU 2020). This provides an example of how electronic payment data could be used to analyse associations between food expenditure and health outcomes.

Results

The average annual fast food transaction frequency was 44 transactions per customer per year (Figure 7.14). By PHN area, customers from Nepean Blue Mountains (NSW), had the highest average annual fast food transaction frequency (58 per year), almost twice the transaction frequency of customers from the PHN area with the lowest, Western Queensland (31 per year).

Figure 7.14: Average annual fast food transaction frequency, by Primary Health Network area, April 2018 – March 2019

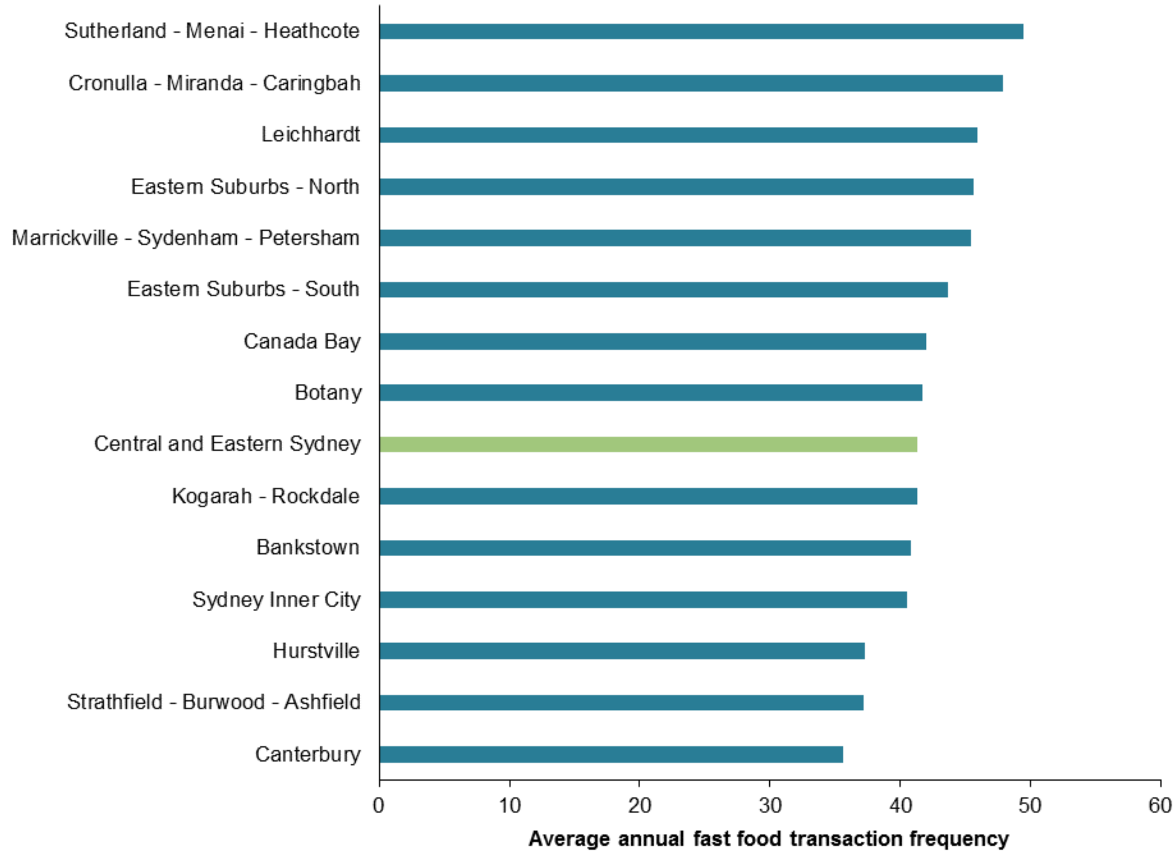


Source: Aggregated electronic payment bank data (April 2018 – March 2019).

Within PHN areas, the average annual fast food transaction frequency varied. The Central and Eastern Sydney (NSW) PHN area can again be used as an example of this. The average annual fast food transaction frequency within the PHN was 41 per year. Of the SA3s within the PHN area that are part of mainland Australia (as the PHN area includes the Lord Howe Island and Norfolk Island SA3s), the average annual fast food transaction frequency ranged from 36 per year in Canterbury to 49 per year in Sutherland - Menai - Heathcote (Figure 7.15).

In the Central and Eastern Sydney (NSW) PHN area, the SA3s with higher average annual fast food transaction frequencies generally contained more higher socioeconomic areas (based on SA1) and those with lower average annual fast food transaction frequencies contained more lower socioeconomic areas (ABS 2018a).

Figure 7.15: Average annual fast food transaction frequency, by Statistical Areas Level 3, Central and Eastern Sydney Primary Health Network area, April 2018 – March 2019



Source: Aggregated electronic payment bank data (April 2018 – March 2019).

There was no clear association between average annual fast food transaction frequency from April 2018 – March 2019 and the prevalence of adult overweight and obesity in 2017–18 by SA3 ($r_s = 0.05$, $p = 0.357$).

Interpretation

The average annual fast food transaction frequency is based on card payments made in person and does not include cash payments, online payments or payments made via food ordering apps. As such, interpretation of differences in average annual fast food transaction frequency between sociodemographic groups is difficult due to differences between groups in the use of electronic payment methods.

Although there appears to be a pattern in the SA3 analysis of the Central and Eastern Sydney (NSW) PHN area towards higher average annual fast food transaction frequency in higher socioeconomic areas, this may in part be due to differences in payment methods. These results may also be influenced by other factors, such as differences in the demographic profile of areas. For example, age, sex, household composition and average household income vary between areas. The results for this PHN area may not be representative of all PHN areas and results may differ depending on the socioeconomic profile of each individual SA3 region.

Although there was no clear association between average annual fast food transaction frequency and the prevalence of adult overweight and obesity, this finding should be interpreted with caution given the limitations of the data sources. For example, in the electronic payment data, there was an inability to determine the items purchased or their quantities or nutritional quality—as an example, it is not possible to distinguish purchasing of a non-discretionary food (such as coffee) from a discretionary food (such as potato chips). Similarly, there is no consensus public health definition as to what is considered ‘fast food’ and different results may occur if a different definition was used and different retailers included.

In addition, the results may also be affected by factors not considered in the analysis, such as socioeconomic position or remoteness area. Different results may also have been seen if a different outcome (such as prevalence of overweight or obesity alone, or prevalence of abdominal overweight or obesity) were used.

Recommendation

Without complementary data on payment methods, electronic payment data related to average annual fast food spend are difficult to interpret. If electronic payment methods are more widely and equally adopted in the future, the data may become more useful as a proxy measure for eating outside of the home.

If this does occur, alternate classifications for retailers could be considered. These include the Food Environment Score tool, an Australian tool that can be used to classify food outlets according to their healthiness (Moayyed et al. 2017a).

At the SA3 level, based on the data sources used and with the acknowledged limitations of the data, a significant correlation between average annual fast food transaction frequency and area-level overweight and obesity was not found. Further exploration at a more granular level may show different results.

Example analysis: Average fast food transaction spend

As with average annual fast food spend and average annual fast food transaction frequency, the average spend per transaction for fast food provides some indication of people’s level of eating out of home.

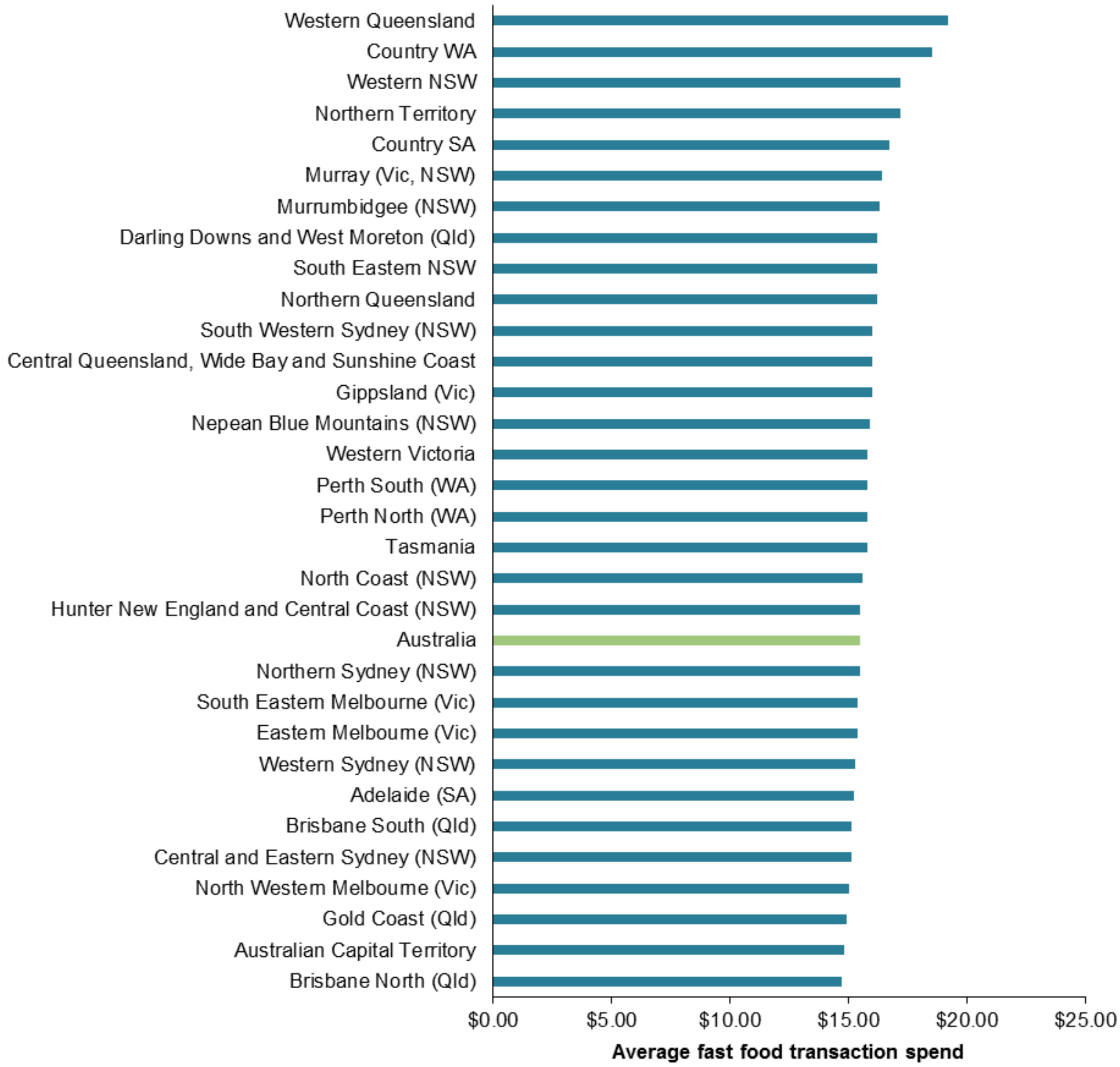
In this analysis, transaction data were analysed to measure the average fast food transaction spend and how this differs between PHN areas and SA3s.

The AIHW compared SA3 data with modelled estimates of the prevalence of adult overweight and obesity by SA3 in 2017–18 (PHIDU 2020). This provides an example of how electronic payment data could be used to analyse associations between food expenditure and health outcomes.

Results

The average fast food transaction spend was $15.50 per transaction (Figure 7.16). By PHN area, the average fast food transaction spend ranged from $14.70 for customers from Brisbane North (Qld) to $19.20 for customers from Western Queensland.

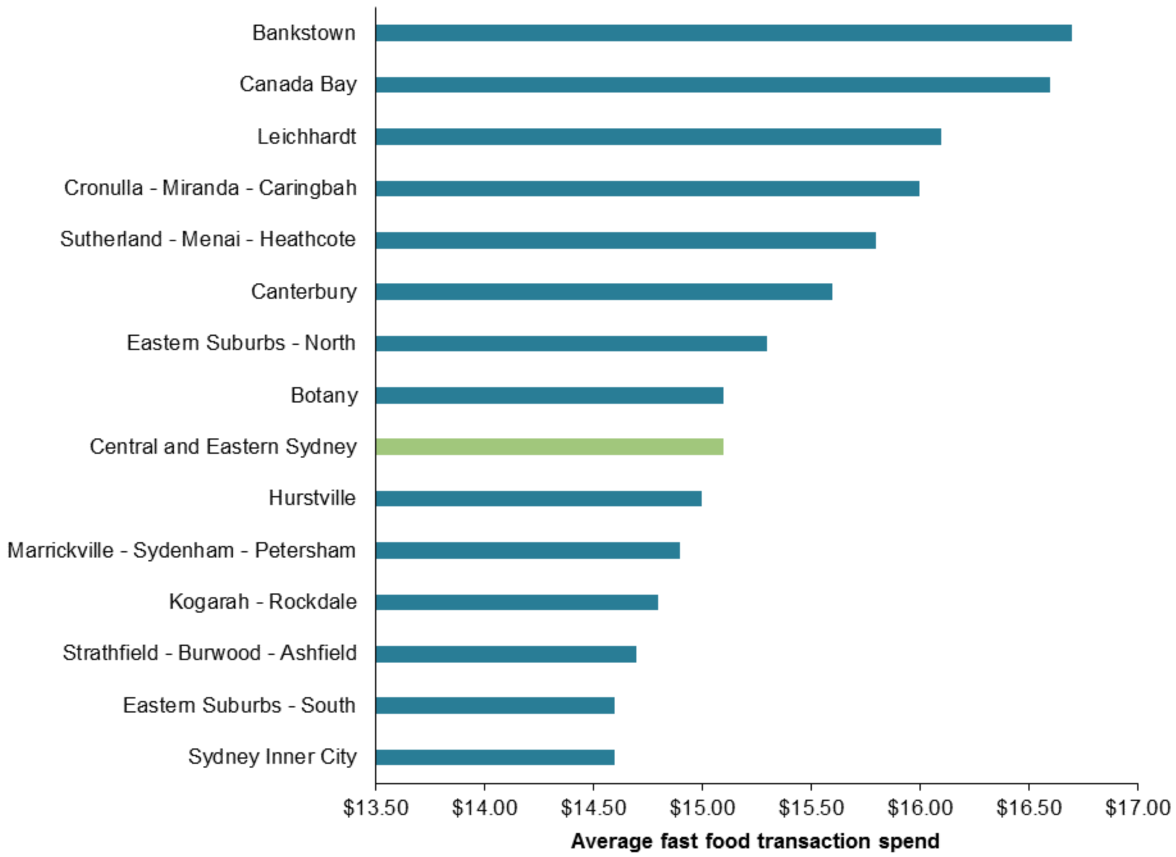
Figure 7.16: Average fast food transaction spend, by Primary Health Network area, April 2018–March 2019



Source: Aggregated electronic payment bank data (April 2018 – March 2019).

Within PHN areas, the average fast food transaction spend may vary. The Central and Eastern Sydney (NSW) PHN area can again be used as an example of this. The average fast food transaction spend within the PHN was $15.10. Of the SA3s within the PHN area that are part of mainland Australia (as the PHN area includes the Lord Howe Island and Norfolk Island SA3s), the average fast food transaction spend varied only slightly, from $14.60 in Sydney Inner City and Eastern Suburbs - South to $16.70 in Bankstown (Figure 7.17).

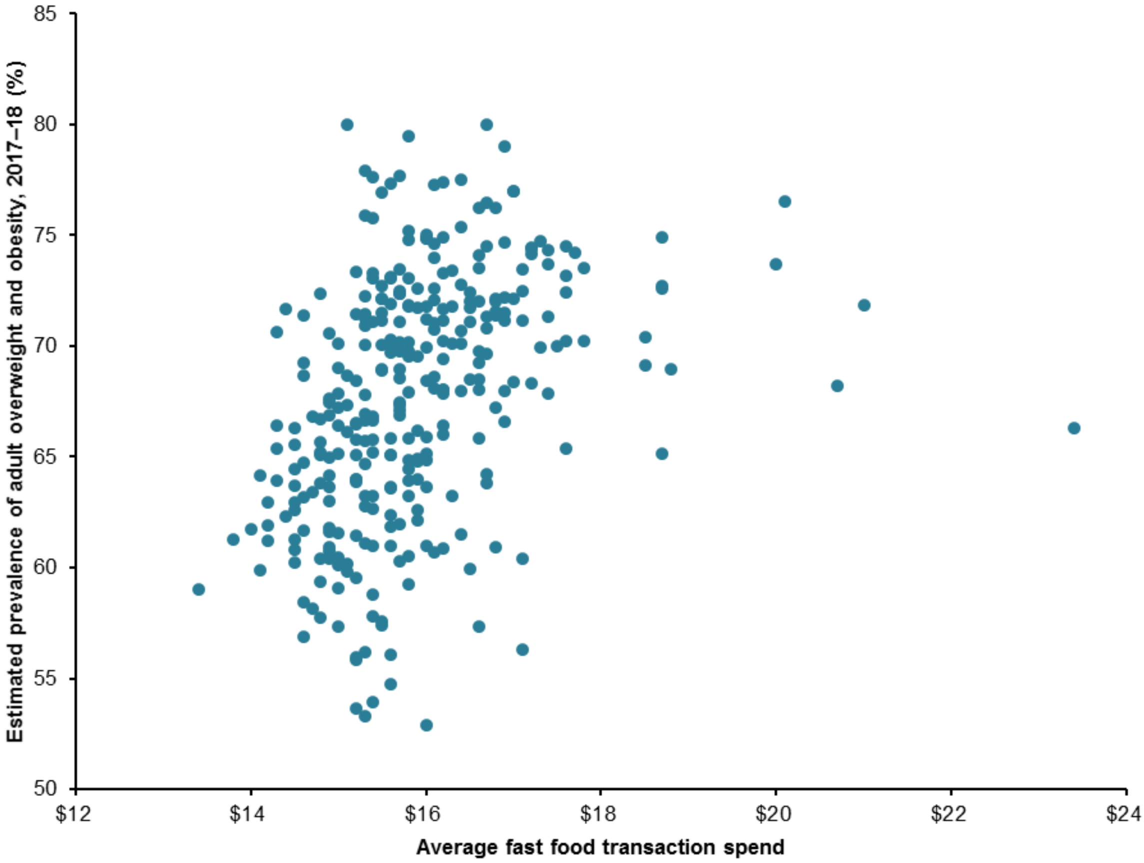
Figure 7.17: Average fast food transaction spend, by Statistical Areas Level 3, Central and Eastern Sydney Primary Health Network area, April 2018 – March 2019



Source: Aggregated electronic payment bank data (April 2018 – March 2019).

There was a weak-moderate positive correlation between average fast food transaction spend for April 2018 – March 2019 and the estimated prevalence of adult overweight and obesity in 2017–18 by SA3 (r_s = 0.49, p < 0.001) (Figure 7.18). That is, SA3s with a lower average fast food transaction spend tended to have a lower prevalence of overweight and obesity, while those with a higher average tended to have a higher prevalence.

Figure 7.18: Estimated prevalence of adult overweight and obesity (2017–18) and average fast food transaction spend (April 2018 – March 2019), by Statistical Areas Level 3



Source: AIHW analysis of aggregated electronic payment bank data (April 2018 – March 2019) and PHIDU 2020.

Interpretation

The average fast food transaction spend is based on card payments made in person and does not include cash payments, online payments or payments made via food ordering apps. As such, interpretation of differences in average fast food transaction spend between sociodemographic groups is difficult due to differences between groups in the use of electronic payment methods.

By SA3, higher average fast food transaction spend for April 2018–March 2019 was associated with a higher estimated prevalence of adult overweight and obesity in 2017–18. This relationship, could in part, reflect other factors which may be related to both average fast food transaction spend and overweight and obesity.

As an example, several of the SA3s with the highest average fast food transaction spends were classified as *Outer regional* areas or *Remote* areas, while several of those with the lowest were *Major cities*, suggesting that remoteness area may be related to both average fast food transaction spend and overweight and obesity. A higher average fast food transaction spend could potentially indicate purchasing of larger quantities, however, it could also reflect differences in household composition and how many people the purchase was for.

There is no consensus public health definition as to what is considered ‘fast food’ and different results may occur if a different definition was used and different retailers included. The results may also be affected by factors not considered in the analysis, such as socioeconomic position or remoteness area (as discussed above).

Different results may also have been seen if a different outcome (such as prevalence of overweight or obesity alone, or prevalence of abdominal overweight or obesity) were used.

Recommendation

Without complementary data on payment methods or household composition, electronic payment data related to average fast food transaction spend are difficult to interpret.
If electronic payment methods are more widely and equally adopted in the future, the data may become more useful as a proxy measure for eating outside of the home.

If this does occur, alternate classifications for retailers could be considered. These include the Food Environment Score tool, an Australian tool that can be used to classify food outlets according to their healthiness (Moayyed et al. 2017a).

The correlation analysis suggests that the relationship between average fast food transaction spend and overweight and obesity could be an area for further research.

Example analysis 3: Location data

This section of the report examines food service density, that is, the number of food services (for example, cafes and restaurants) per 100,000 population, across geographical areas. All analyses in this section were completed by the AIHW.

General methods

Data source

The Australian Tax Office maintains a registry of all businesses operating in Australia (the Australian Business Register (ABR)) who have registered for an Australian Business Number (ABN). The ABR contains information that is publicly available via an online search, and non-public information that is only available to the ABN holder or their tax agent, and eligible government agencies such as federal agencies, state/territories departments and local governments (ABR 2018).

Publicly available information includes details of the business such as ABN, registered business name, trading name and state and postcode of the main business. Information that is not publicly available includes the Business Industry Code and description, and the business location address and geocode. The Business Industry Code used by the ABR is based on the ANZSIC coding system with an additional digit. These codes are used for tax and reporting purposes.

Individuals or their representatives can apply for an ABN online via the ABR website (ABR 2018). During the ABN registration process, applicants are asked to describe the main business activity in a free text field, and then select from a list of suggested categories that best matches the main business activity. For example, 'fish and chip shop' results in a number of options, the first being 'Take away chicken, fish and chips, hot pies or pizza retailing - cooked ready to eat'. This information is then used to classify the business into an ANZSIC code.

Businesses with multiple locations are listed multiple times on the register—once for each location.

Data as at 30 August 2019 were used for this report.

Classification into industry groups

For these analyses, businesses registered as active on the ABR with an ANZSIC code of 4511 ('Cafes and Restaurants') or 4512 ('Takeaway Food Services') were selected. These businesses will be collectively referred to as 'food services' (Department of Agriculture Fisheries and Forestry 2012).

Analysis by Statistical Area Level 3 region

The location data were analysed by SA3 region based on geocode latitude and longitude of the business address. Approximately 13% (11,000) of businesses did not have a geocode latitude and longitude and were unable to be reliably mapped to a location. These businesses were excluded from the analyses.

The locations of businesses recorded on the ABR may represent actual locations or mailing addresses, corporate offices or seasonal addresses. As such, there may be some misclassification of location, however, the extent and direction of this is unknown.

Each business was mapped to an SA3 using the latitude and longitude. There are 358 SA3 regions. Non-spatial SA3s and those with no population were excluded (for example, Illawarra Catchment Reserve), leaving 336 SA3s in the analyses (ABS 2016a).

The density of food services per 100,000 persons was calculated for each SA3 as the number of food services divided by the 2018 population estimate (ABS 2019e). SA3 areas were also classified into Greater Capital City area and Rest of State (ABS 2016a).

Correlation with overweight and obesity

Correlations between food service density and modelled estimates of the prevalence of adult overweight and obesity in 2017–18 (PHIDU 2020) were explored for SA3 areas.

General considerations for interpretation of location data analysis

The following considerations apply to the example analyses presented in the following text and should be kept in mind when interpreting the data.

Data coverage

Data from administrative sources such as the ABR can misrepresent the number of food services in an area in a number of ways, including by:

- including services that are no longer open
- missing services altogether (for example, if they are operating without an ABN or if they serve food but not as their main business activity so do not have one of the ANZSIC codes selected)
- having incorrect or missing business location information.

For these reasons validation against primary data is often recommended (Ni Mhurchu et al. 2013), however, this was out of scope for the current report.

The ABR is aware that many people forget to cancel their ABN when they cease operating their business (ABR 2019). The ABR uses tax return and business activity statement lodgement information to establish whether a business is still operating, and cancels ABNs when it establishes that a business has ceased. To avoid including businesses that were no longer in operation but that had not yet been removed from the ABR, the data extraction was limited to businesses registered for goods and services tax (generally those with a turnover of $75,000 or more).

Therefore, the data used in these analyses are limited to businesses on the ABR that met the following criteria:

- had an active ABN
- were registered for goods and services tax
- had an ANZSIC code of 4511 or 4512
- had a geocode longitude and latitude for their business location.

Classification into industry codes

These analyses were based on ANZSIC codes 4511 (‘Cafes and Restaurants’) and 4512 (‘Takeaway Food Services’). An ANZSIC code is assigned to each business based on the main business activity reported by the individual registering the business and does not consider the nutritional quality of foods available through the business. It is likely that many businesses offer both healthy and unhealthy food options.

Business size

Examining the size of each business was outside of the scope of the current report. However, an area with 2 small businesses may service the same number of people as 1 large business in another area. This would result in a lower food service density in areas with a number of large businesses when compared to areas with multiple small businesses even if the number of people serviced in each area is similar.

Comparisons between areas

The size of SA3s across Australia range from 11 to 714,500 square kilometres, with population densities ranging from less than 0.1 to 9,900 people per square kilometre in 2018 (ABS 2016a, 2019f). Therefore, the ability to show the extent of the variation in food service density that exists within and between SA3 areas is limited.

Example analysis: Density of food services by region

The food environment can influence food choices and dietary behaviours (Mahendra et al. 2017; Ni Mhurchu et al. 2013). There is a growing interest in measuring local food environments (including the type, availability and accessibility of food outlets), with the assumption that people use the services that are close to them. The most commonly used measures of the local food environment are density (number of outlets per population or geographic area), proximity (distance between a location such as home and an outlet) or variety (the mix of outlets within an area).

These analyses measure the density of 'food services' ('Cafes and Restaurants' and 'Takeaway Food Services' combined) in relative terms: that is, the number of food services per 100,000 population by SA3, and within defined geographic areas. They also explore associations between food service density in Australia and the prevalence of overweight and obesity.

For these analyses the median (middle number) has been presented, along with the interquartile range (IQR), which represents the range of the middle 50% of the data. This is presented here as the 25th percentile value and the 75th percentile value. The median and IQR are reported along with the average (mean) and standard deviation (SD), as the density of food services is skewed upwards by some SA3s with extremely high densities. The median and IQR are more robust measures when there are outliers and can allow for fairer comparisons.

Results

The median density of food services across Australia by SA3 was 221 (IQR 162–311) per 100,000 persons (Table 7.5).

Victoria had the highest median density of food services by SA3 (278 per 100,000 persons), while the Northern Territory had the lowest (129 outlets per 100,000 persons). Across the other states and territories, the median density of food services was quite similar, ranging from 190 to 217 per 100,000 persons.

Table 7.5: Number and density of food services per 100,000 persons, by state or territory, using Statistical Areas Level 3 (SA3s) data, 2019

State/Territory	Number of SA3s	SA3 food services density	
		Average (SD)	Median (IQR)
New South Wales	92	253 (135)	217 (169–310)
Victoria	66	317 (165)	278 (212–346)
Queensland	82	253 (157)	206 (143–314)
Western Australia	34	236 (147)	199 (133–291)
South Australia	28	291 (387)	190 (131–306)
Tasmania	15	238 (128)	212 (160–258)
Australian Capital Territory	10	321 (231)	213 (160–495)
Northern Territory	9	150 (141)	129 (71–196)
Total	336	266 (185)	221 (162–311)

SD: standard deviation; IQR: interquartile range (25th – 75th percentiles).

Source: AIHW Analysis of data from ABR 2019.

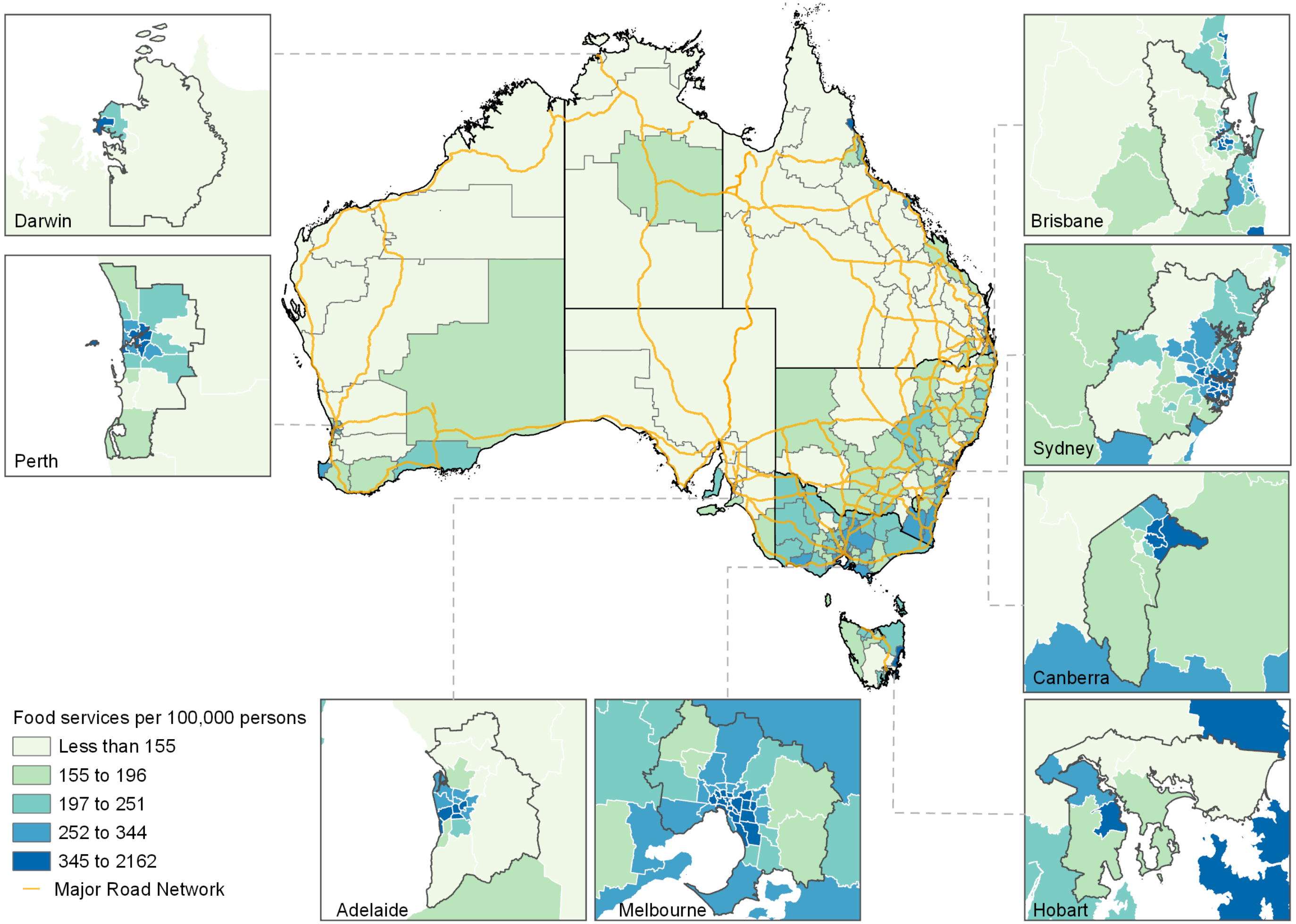
The SA3s with the highest food services density were in capital city centres. Adelaide City had the highest density of food services at 2,162 per 100,000 people, more than twice that of Melbourne City (1,075 per 100,000), Sydney Inner City (991 per 100,000) and Brisbane Inner (937 per 100,000), Canberra East (838 per 100,000) and Perth City (804 per 100,000). Hobart Inner (637 per 100,000) and Darwin City (471 per 100,000) had the lowest food service densities of the capital cities.

The SA3s with the lowest food service densities were in outback Australia. East Arnhem (14 per 100,000) and Daly – Tiwi – West Arnhem (17 per 100,000) in the Northern Territory had the lowest food service density, followed by Far North (Queensland, 60 per 100,000).

Overall, the SA3s that were closer to capital cities tended to have a higher food service density than those in regional areas (Figure 7.19). Across Australia, the density of food services was higher in Greater Capital City SA3s (median: 280 per 100,000; IQR: 186–383), compared with Rest of State SA3s (median: 186 per 100,000; IQR: 145–238).

In some cases higher food service density may be reflective of areas with tourist or shopping destinations or major road network routes. For example, the 2 SA3s with the highest food service densities outside the Greater Capital City areas are major tourist destinations: Surfers Paradise (651 per 100,000) and Noosa (564 per 100,000). Barkly in the Northern Territory has a relatively high food service density (196 per 100,000), however, all but 1 food service in Barkly is in the town of Tennant Creek, which is on the only major highway between Darwin and Alice Springs.

Figure 7.19: Density of food services (number of outlets per 100,000 persons) in Australia, and capital cities, by quintiles, by Statistical Areas Level 3



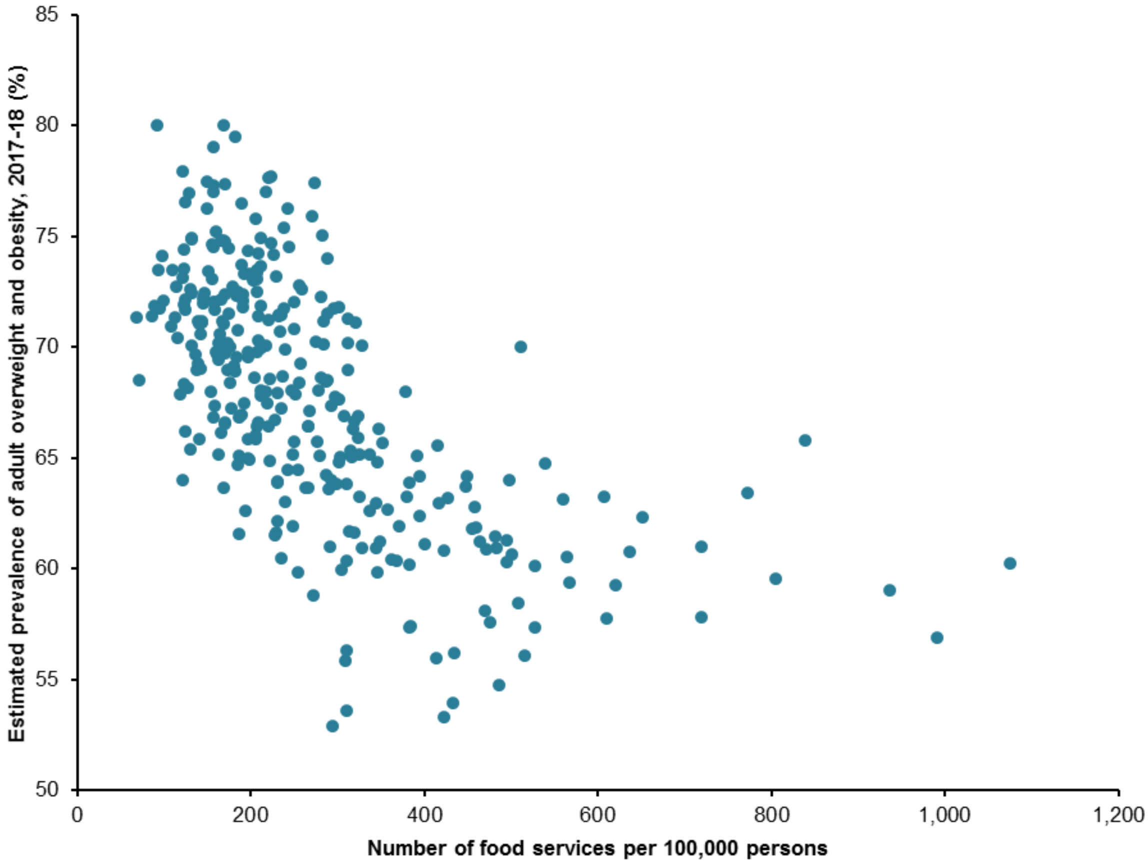
Note: Maps are for illustration purposes only and are not to scale.

Source: AIHW analysis of data from ABR 2019.

Results of correlations with overweight and obesity

There was a moderate-strong negative correlation between the density of food services and the prevalence of overweight and obesity by SA3 ($r_s = –0.68$, $p < 0.001$) (Figure 7.20). That is, as the density of food services increased, the prevalence of overweight and obesity decreased.

Figure 7.20: Estimated percentage of people aged 18 years and over who were overweight or obese (2017–18), with food services density per 100,000 persons (2019), by Statistical Areas Level 3



Note: Adelaide City (SA) (2,162 outlets per 100,000 persons) not shown.

Source: AIHW analysis of data from ABR 2019 and PHIDU 2020.

To further explore the association between food service density and the prevalence of overweight and obesity, additional correlations were undertaken for Greater Capital City SA3s (n = 186) and Rest of State SA3s (n = 150). While the negative correlation remained for both, it was strong for Greater Capital City SA3s ($r_s = –0.77$ and $p < 0.001$) and weak for Rest of State SA3s ($r_s = –0.31$ and $p < 0.001$).

Interpretation

In general, SA3s that were closer to capital cities had higher densities of food services than those in more regional locations. Overall, the food service density in Australia using administrative data from the ABR ranged from 14 per 100,000 people in outback Northern Territory, to 2,162 per 100,000 people in Adelaide City. It should be noted that there is currently no consensus on what is considered a high or low density of food outlets.

Previous research has found a similar relationship between food service density across geographical areas. For example, food outlet density in Victoria was highest in areas located closest to Melbourne's CBD (urban Victoria) and lowest in regional Victoria (Needham et al. 2020).

Comparisons with the food service density of other countries is difficult due to differences in the classification of food outlets and/or geography. For example, Public Health England used administrative data to calculate the density of fast food outlets in England and found it ranged from 26 to 232 per 100,000 people across Local Health Authorities as at 31 December 2017 (Public Health England 2018). However, they included supermarkets/hypermarkets in their consideration of 'fast food outlets' while the ANZSIC codes used in our example analyses do not capture these retailers. These differences need to be taken into account when interpreting food service density variation across studies.

These analyses indicate that SA3s with a higher food service density tended to have a lower prevalence of overweight and obesity. However, a review of the literature regarding the relationship between food service density and overweight and obesity produced mixed findings (Gordon-Larsen 2014). Therefore, other factors within areas of high food service density may be of importance when considering rates of overweight and obesity.

For example, areas with food swamps (where less healthy food options inundate healthy food options) have been associated with adult obesity (Cooksey-Stowers et al. 2017). An Australian study found that residents of areas where fast food outlets made up greater than 25% of all food outlets had a higher mean body mass index (Feng et al. 2018). It may therefore not be the food service density per se that is related to overweight and obesity, but the quality of food offered within those areas of density.

The variations in the density of food services between areas can be difficult to interpret without knowledge of the geographical areas in question, as areas with high densities may reflect areas where people work or shop rather than where they live (that is, areas with relatively low populations but high levels of amenities). For example, the Canberra East (ACT) SA3, has a small population but a relatively high food service density of 838 per 100,000 persons. However, the Canberra East SA3 contains a shopping centre, Canberra's airport, and a number of light industrial areas.

There are also a number of other factors not explicitly considered here that have been mentioned earlier in this chapter and in Box 7.1. These include things such as household composition and the size of businesses within each area, which may influence the density of food services within an area and associations with overweight and obesity.

Recommendation

If food service density data from administrative data such as the ABR are to be used to measure the food environment, it would be recommended to validate the accuracy of the data source. Some areas of focus would be establishing the number of services listed on the ABR that are no longer operating, the number of services that are not on the ABR (either at all, or with a food service ANZSIC code), and the number that have incorrect or missing business information (such as location and ANZSIC code).

It would also be useful to determine an appropriately sized area around places of residence to represent the true space where people live and interact (Ni Mhurchu et al. 2013). Area-based measures such as those used in these example analyses (SA3s) can be large enough that they cover multiple communities with differing characteristics (for example, age or socioeconomic position), making it difficult to obtain clear insights about the residents within the region. However, the use of smaller geographic areas (for example, SA1s) may not sufficiently capture the services that residents use. For example, SA1s are usually a portion of a suburb and people are likely to shop in neighbouring suburbs for food as well as their own.

Additional information on the food environment may also improve interpretation of the food service density data presented here. Some research has assessed ratios of food services to supermarkets which may be important when assessing the food environment of an area (Cooksey-Stowers et al. 2017; Moayyed et al. 2017b). Moayyed and colleagues (2017b) assessed the food environment across 10 suburbs of the Illawarra region of New South Wales. They found that living in areas of higher food quality (more green grocers/ supermarkets and fewer fast food franchises) was associated with healthier eating behaviours (for example, eating more fruits and vegetables). Additionally, the mix of food services available has been associated with obesity and income, such that people living in areas of high takeaway exposure (more takeaway stores relative to other food outlets) and in areas of low income, had more frequent processed meat consumption and greater odds of being obese (Burgoine et al. 2018). Measures of food service density may be used more effectively when used alongside measures of the quality of services or foods provided and consumer purchasing behaviour (Gordon-Larsen 2014).

The ANZSIC codes selected for these analyses (4511 ‘Cafes and Restaurants’ and 4512 ‘Takeaway Food Services’) cover a wide range of food outlets and do not consider the nutritional quality of foods available. There are also other outlets such as service stations that provide easy access to unhealthy food options that could be included in measures of the food environment. Alternate classifications that could be considered include the Food Environment Score tool, an Australian tool that can be used to classify food outlets according to their healthiness (Moayyed et al. 2017a).

Finally, the exclusion of areas of low population but high food service density may aid the interpretation of differences between areas.

8 Conclusion

This chapter summarises some of this report’s key findings for the future use of novel data sources for monitoring food and nutrition.

Novel data sources can complement, but not replace, more traditional data sources

This report highlighted some cases where novel data sources could be used to complement traditional data sources, particularly in the interim periods between collections of traditional data. This includes using purchase data to monitor energy purchased from discretionary foods and to monitor leading contributors to purchased energy, saturated fat and sodium.

However, given the various limitations of novel data sources, they are not a replacement for more traditional data sources typically used in food and nutrition monitoring. In particular, with the exception of app and wearable device data, none of the novel data sources are able to provide individual-level information about food and physical activity behaviours, as can be obtained from population nutrition surveys.

Novel data sources offer some advantages over traditional data sources

A major advantage of many of the novel data sources is that data are continuously collected. Many of the surveys typically used in food and nutrition monitoring are infrequently and/or irregularly conducted, and novel data sources have the potential for more frequent, regular and timely data provision, allowing for more frequent and regular monitoring of trends over time.

Nutrition surveys are also expensive to administer and have high participant burden which influences the number and type of participants involved. In comparison, many novel data sources cover a wider proportion of the population and require minimal involvement on behalf of the participant.

A third key advantage of some of the novel data sources discussed in this report (such as point-of-sale scanner data) is that data collection is prospective and not subject to social desirability or recall biases that affect other sources of food and nutrition data, such as population nutrition surveys. An exception to this is data on foods and drinks recorded as consumed by users of apps, which is likely to still be subject to biases, through accidental or deliberate omission of foods and drinks by users, errors in selection of foods and drinks, and errors in estimation of portion sizes.

Data coverage and representativeness are key issues for novel data sources

A key limitation of many of the novel data sources discussed in this report is a lack of data coverage and/or representativeness. Purchase data may be limited to purchases at certain retailers and electronic payment data to customers of certain banks, while data from smartphones and wearable technologies are from only individuals who have chosen to use these. Often there is not sufficient sociodemographic data to assess how representative the resulting data are of the general population.

In some cases, novel data may be able to be weighted to better represent the population of interest. However, in other cases, there may be a lack of, or insufficient collection of, the demographic characteristics needed to adjust the data (Seeskin et al. 2018).

Transparency of data collection and analysis methods and commercial sensitivities are key issues for novel data sources

Many of the novel data sources discussed in this report involve privately held data. A limitation of using privately held data is a potential lack of transparency and documentation of data collection and/or analysis methods. The information needed to provide adequate explanations of the sources and limitations of such data may not be publicly available (Seeskin et al. 2018) and/or data providers may restrict the publication of detailed methods (Bandy et al. 2019). For example, there may be limited information around definitions used and descriptions of key variables, which can make it difficult to interpret findings from the data collected.

Data providers may also have restrictions on the use of data—as an example, retailers may or may not be willing to share data for research of negative health consequences from retail sales (Morris et al. 2018).

Novel data sources should be validated against more traditional data sources

Given some of the data quality issues previously mentioned, novel data sources should be validated against more traditional data sources, where possible.

Some differences in results between novel data sources and more traditional data sources may be reasonably explained, including where there are limitations to some of the more traditional data sources (such as biases in self-reported data) (Hicks et al. 2019). Given this, a comparison that shows similar trends across time or sociodemographic groups, but with differences in magnitude, may sometimes provide sufficient validation.

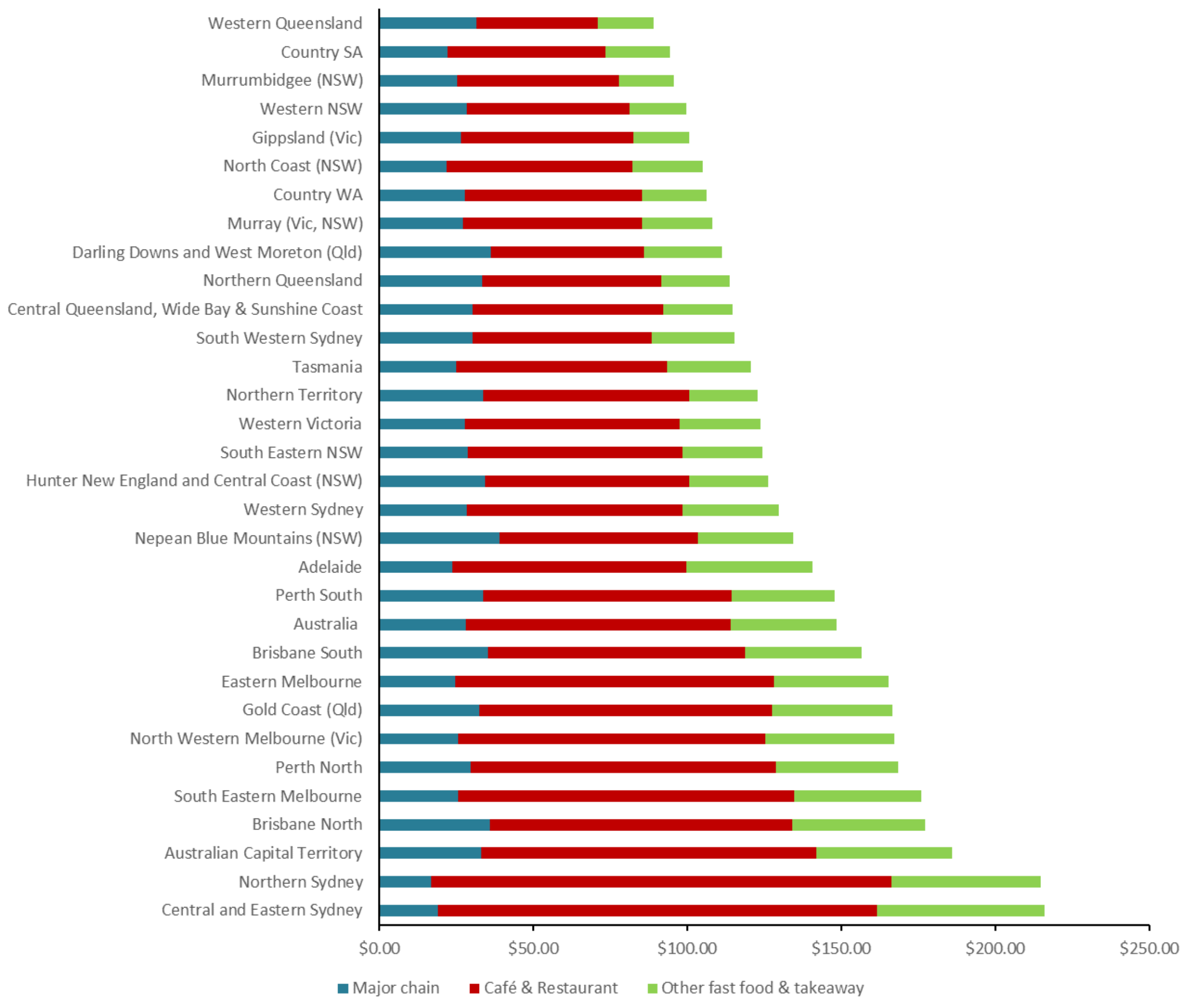
The quality of novel data sources should be assessed for specific research questions

The ‘fitness for purpose’, or quality, of a data source should be assessed against the intended aims of the outputs. The ABS Data Quality Framework provides a standard for assessing the quality of statistical information (ABS 2009). The fitness for purpose of the novel data sources discussed in this report will vary depending on the specific research question they are used for and may vary for data collections of the same type.

Given this, the quality of a novel data source should be assessed for its specific research question. Considerations might include transparency of data production, who or what the data represent, who or what is excluded, and sources of error (including biases), among others (ABS 2009).

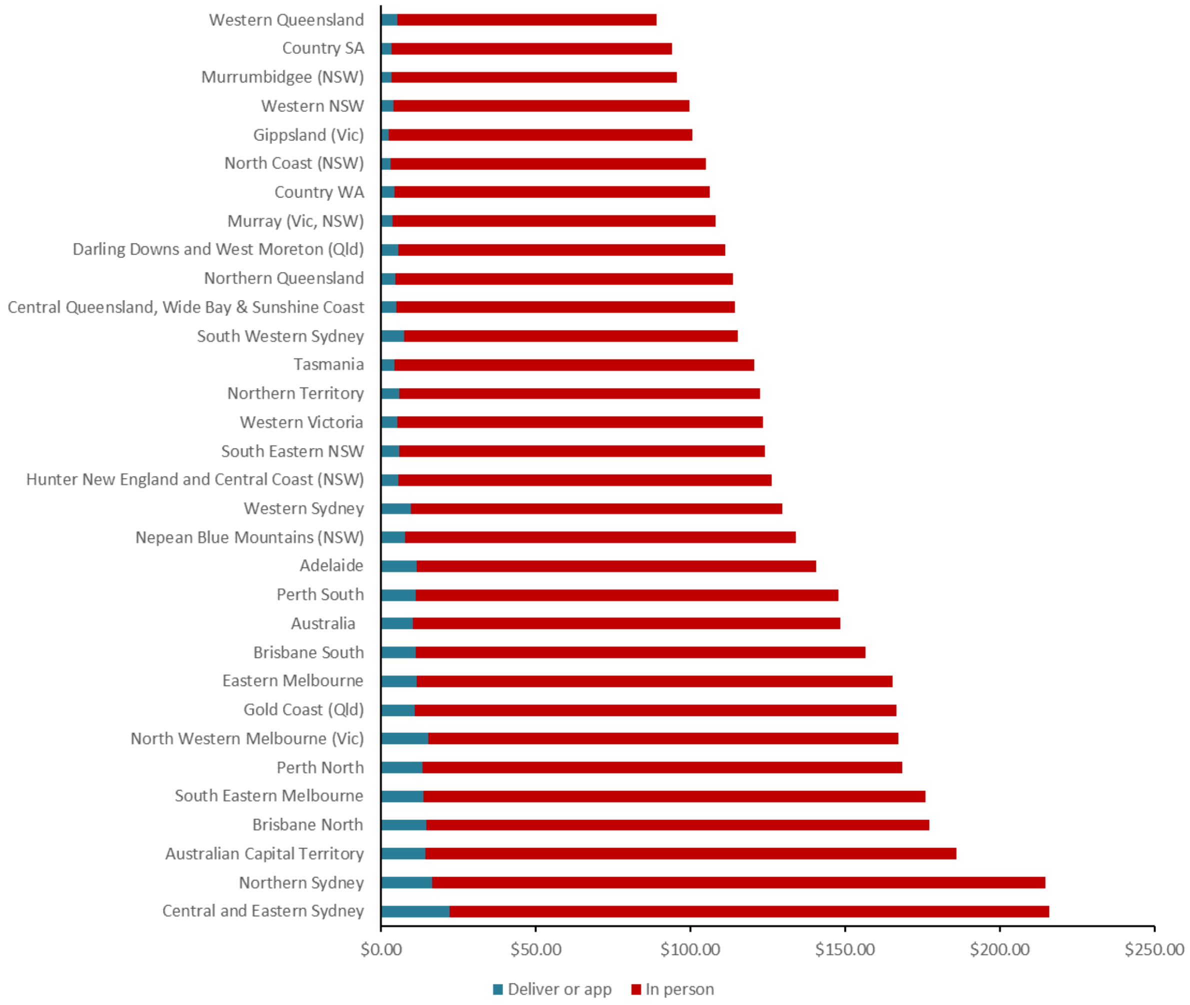
Appendix A: Additional figures

Figure A.1: Average monthly dining out spend, by Primary Health Network area and establishment type, 2018



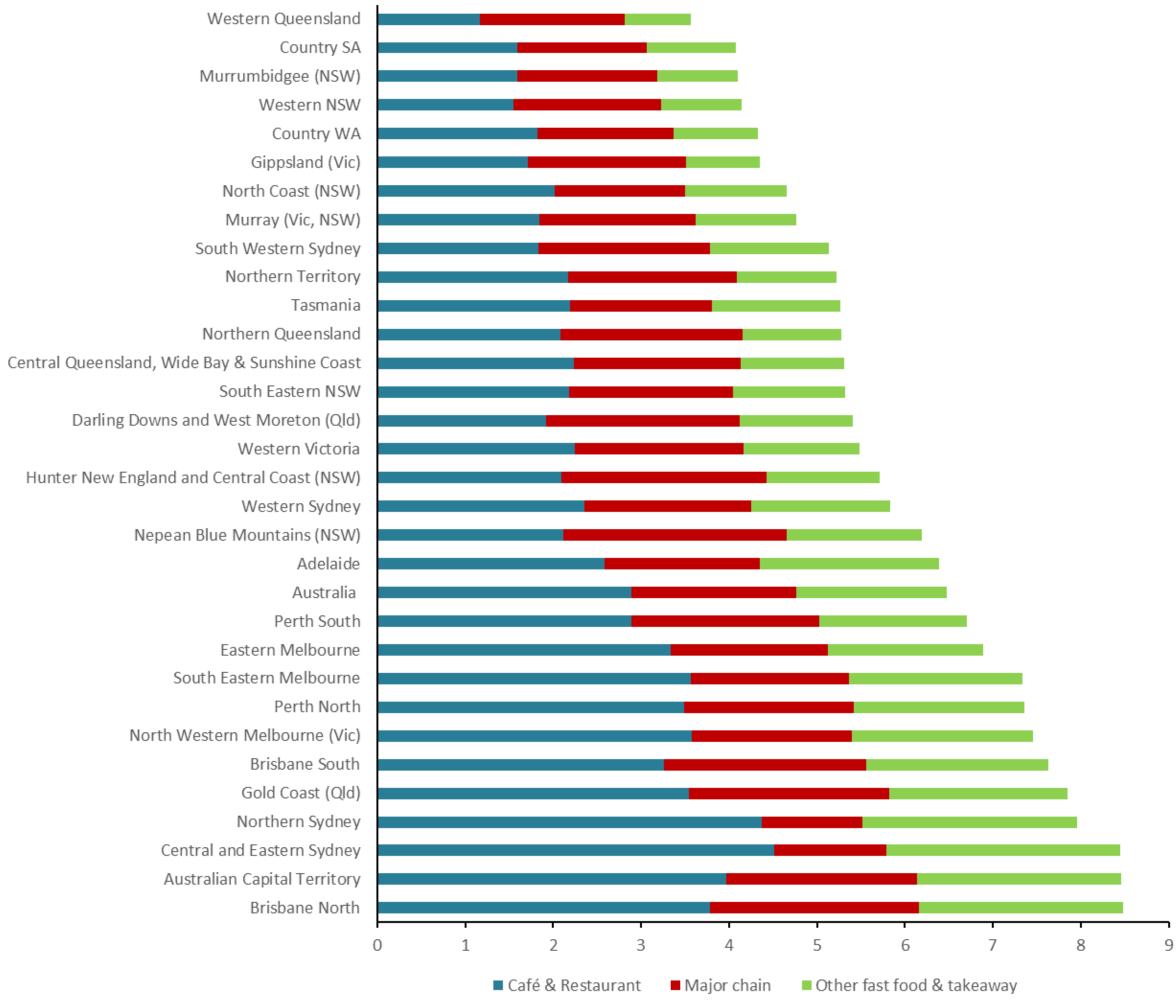
Source: Data provider analysis of electronic payment data.

Figure A.2: Average monthly dining out spend, by Primary Health Network and payment type, 2018



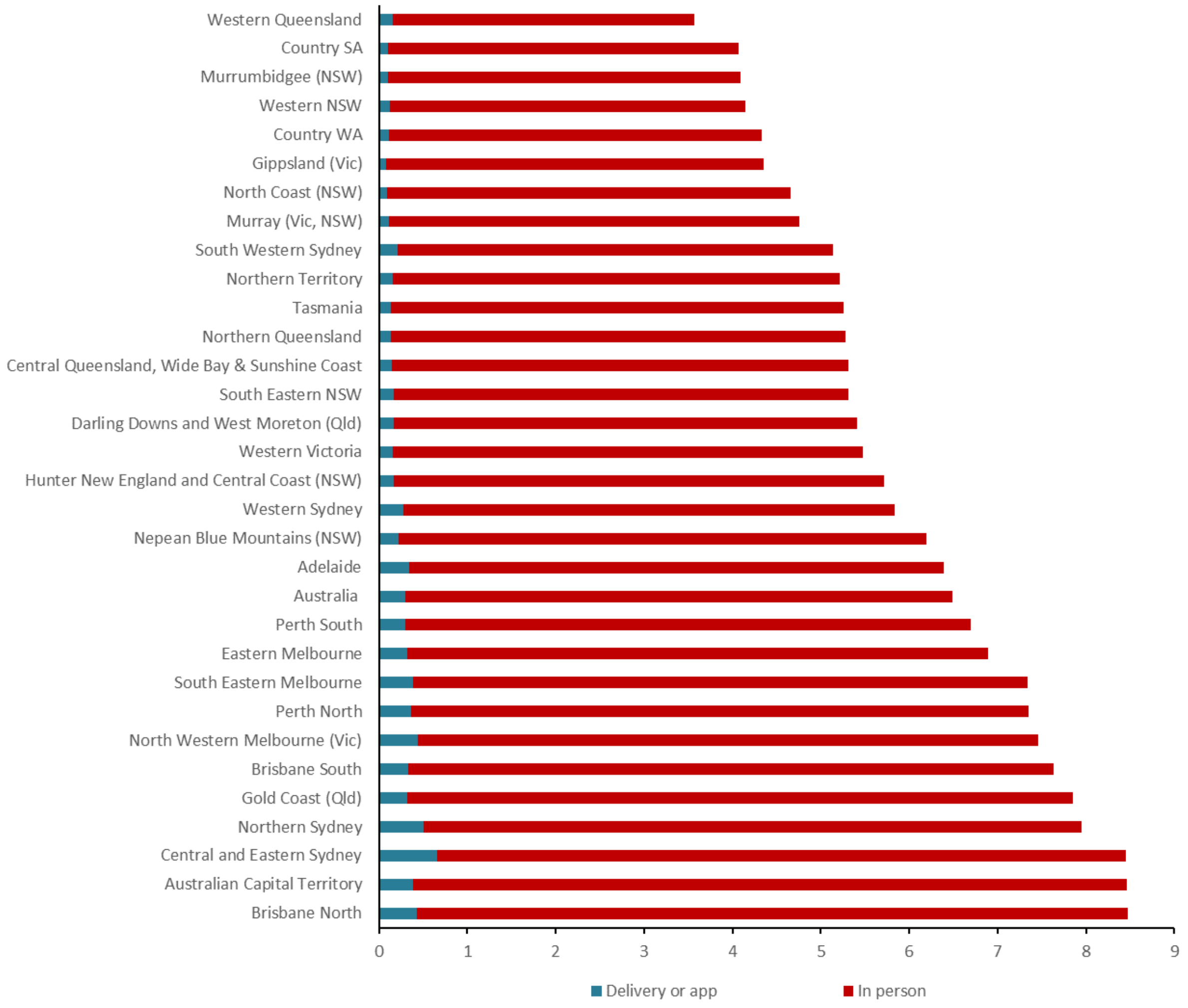
Source: Data provider analysis of electronic payment data.

Figure A.3: Average monthly dining out transaction frequency, by Primary Health Network area and establishment type, 2018



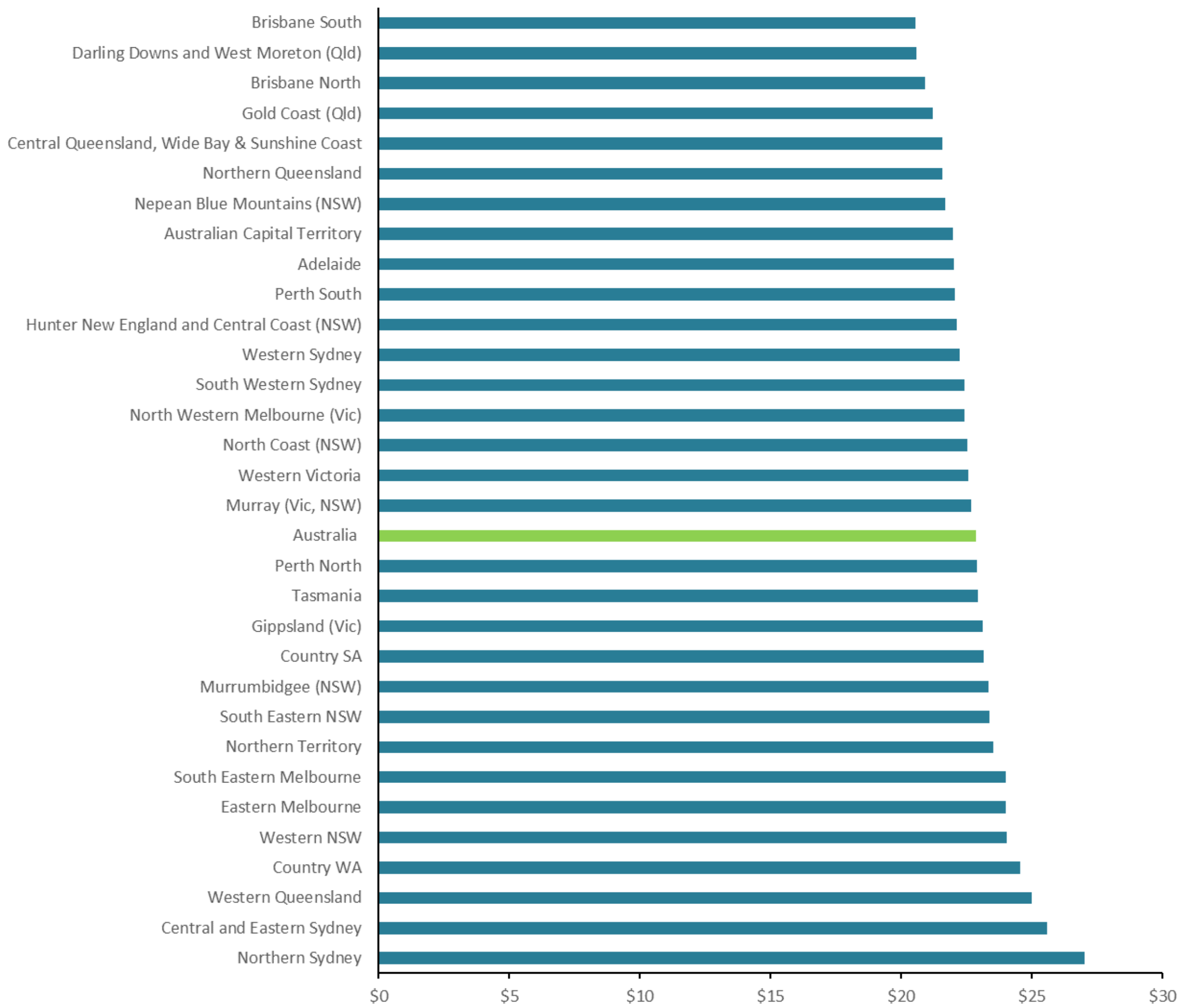
Source: Data provider analysis of electronic payment data.

Figure A.4: Average monthly dining out transaction frequency, by Primary Health Network and payment type, 2018



Source: Data provider analysis of electronic payment data.

Figure A.5: Average dining out transaction value, by Primary Health Network area, 2018



Source: Data provider analysis of electronic payment data.

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Abbreviations

ABN	Australian Business Number
ABR	Australian Business Register
ABS	Australian Bureau of Statistics
ACT	Australian Capital Territory
App	software application
AIHW	Australian Institute of Health and Welfare
ANZSIC	Australian and New Zealand Standard Industrial Classification
ASGS	Australian Statistical Geography Standard
AUSNUT	Australian Food, Supplement and Nutrient Database
BPAY	bill payment
CPI	Consumer Price Index
EFTPOS	electronic funds transfer point of sale
FSANZ	Food Standards Australia New Zealand
GCCSA	Greater Capital City Statistical Area
GPS	global positioning system
HES	Household Expenditure Survey
IQR	interquartile range
NHMS	National Health Measures Survey
NHS	National Health Survey
NNPAS	National Nutrition and Physical Activity Survey
NNS	National Nutrition Survey
NSW	New South Wales

NT	Northern Territory
PHIDU	Public Health Information Development Unit
PHN	Primary Health Network
Qld	Queensland
SA	South Australia
SA1	Statistical Area Level 1
SA2	Statistical Area Level 2
SA3	Statistical Area Level 3
SD	standard deviation
Vic	Victoria
WA	Western Australia

Symbols

<	less than
%	per cent
$	Australian dollars
p	probability value
r	Pearson correlation coefficient
r_s	Spearman's rank correlation coefficient

Glossary

Australian Statistical Geography Standard (ASGS): Common framework defined by the Australian Bureau of Statistics for collecting and disseminating geographically classified statistics. It replaced the Australian Standard Geographical Classification (ASGC) in July 2011.

discretionary foods: Foods and drinks not necessary to provide the nutrients the body needs, but which may add variety. Many are high in saturated fats, sugars, salt and/or alcohol, and are energy dense.

Greater Capital City Statistical Area (GCCSA): A component of the Australian Statistical Geographical Standard (ASGS) which represents the functional extent of each of the eight state and territory capital cities. There are 16 spatial GCCSAs covering the whole of Australia—8 regions representing each of the Australian state and territory capital cities and 8 regions covering the rest of each state, the Northern Territory, and other territories.

interquartile range: A measure of variability, based on dividing a data set into quartiles. Quartiles divide a rank-ordered data set into four equal parts. The values that divide each part are called the first, second, and third quartiles; and they are denoted by Q1, Q2, and Q3, respectively.

mean: The sum of the value of each observation in a data set divided by the number of observations. This is also known as the arithmetic average.

median: The midpoint of a list of observations that have been ranked from the smallest to the largest. The median age, for example, is the age point at which half the population is older than that age and half is younger than that age. See also **interquartile range**.

Primary Health Network: Primary Health Networks were established on 1 July 2015. These networks are intended to play a critical role in connecting health services across local communities so that patients, particularly those needing coordinated care, have the best access to a range of health-care providers, including practitioners, community-health services and hospitals. Primary Health Networks work directly with general practitioners, other primary-care providers, secondary-care providers and hospitals.

remoteness areas: These regions are defined by the Australian Statistical Geographical Standard (ASGS) and based on the Accessibility/Remoteness Index of Australia which uses the road distance to goods and services (such as general practitioners, hospitals and specialist care) to measure relative accessibility of regions around Australia.

Statistical Area Level 3 (SA3): A component of the Australian Statistical Geographical Standard (ASGS) and designed for the output of regional data. SA3s create a standard framework for the analysis of ABS data at the regional level through clustering groups of Statistical Areas Level 2 (SA2s) that have similar regional characteristics, administrative boundaries or labour markets. SA3s generally have populations between 30,000 and 130,000 persons. They are often the functional areas of regional towns and cities with a population in excess of 20,000, or clusters of related suburbs around urban commercial and transport hubs within the major urban areas. SA3s are aggregations of whole SA2s.

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Related publications

The following AIHW publications relating to food and nutrition might also be of interest:

- AIHW 2019. Poor diet. Cat. no. PHE 249. Canberra: AIHW.
- AIHW 2018. Nutrition across the life stages. Cat. no. PHE 227. Canberra: AIHW.

Novel data sources—in the context of food and nutrition monitoring—are sources of data that were not collected for statistical purposes and are yet to have been extensively used for these purposes. This report explores novel sources of data that can be used to monitor food and nutrition, including market share data, purchase data, electronic payment data, location data, and app and wearable device data. It also provides some example analyses using purchase data, electronic payment data and location data.

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