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Data visualization by alluvial diagrams for bibliometric reports, systematic reviews and meta-analyses

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Alluvial diagram is a type of flow diagram traditionally used to illustrate the temporal changes in a network composition. However, alluvial diagram can also be utilized as a graphical summary of the demographic data of studies included in a bibliometric report, systematic review or meta-analysis. Such a graphical summary enables readers to quickly discover data patterns and notice the relationships between adjacent data columns. The current study demonstrates such an application of the alluvial diagram and discusses how it facilitates readers to better comprehend the data presented.

Keywords: Alluvial diagram, bibliometrics, meta-analysis, neuroimaging, taste.

SYSTEMATIC reviews and meta-analyses are often considered to be of the highest level of scientific evidence in the hierarchy of academic research[1]. Meanwhile, bibliometric reports allow qualitative and quantitative evaluation of research output on specific topics[2–4] and are now used to evaluate individual researchers and institutions[5,6]. These publications help readers quickly identify and digest the most important and relevant research findings summarized from a vast amount of scientific literature. However, such publications are often long and tedious and the details of the data are usually presented in large tables. Readers may take time to digest the details of information contained in the tables to compare and contrast, and eventually discover data patterns. Meanwhile, alluvial diagram is a type of flow diagram traditionally used to illustrate the temporal changes in a network composition, for example, changes in the structures of scientific disciplines or changes in the usage of words over time[7–9]. However, alluvial diagram can also be utilized as a graphical summary of the background or demographic data of the studies included in bibliometric reports, systematic reviews or meta-analyses. Therefore, this study aims to demonstrate such bibliometric application of the alluvial diagram and discuss how it facilitates readers to better comprehend the data presented.

This study used two examples to illustrate the usefulness of alluvial diagrams in reorganizing and displaying data.

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Table 1. Demographic data from 16 studies included in a meta-analysis compiled in Excel spreadsheet for generation of an alluvial diagram

Study	Sample size (binned)	Sex predominance	Mean age (binned)	Fasting time before experiment	Sweet	Sour	Bitter	Salty	Umami
O'Doherty *et al.* (2001)	1–10	Unknown	Unknown	Unknown	Yes	No	No	Yes	No
Small *et al.* (2003)	1–10	More females	21–25	Unknown	Yes	No	Yes	No	No
Haase *et al*. (2007)	11–20	Equal sex ratio	21–25	Unknown	Yes	No	No	No	No
McCabe and Rolls (2007)	11–20	Equal sex ratio	Unknown	Unknown	No	No	No	Yes	Yes
Veldhuizen *et al.* (2007)	11–20	More females	26–30	Unknown	Yes	Yes	No	Yes	No
Kami *et al.* (2008)	1–10	More females	36–40	Unknown	Yes	No	No	No	No
Bender *et al.* (2009)	11–20	More females	21–25	Unknown	Yes	Yes	No	Yes	No
Haase *et al.* (2009)	11–20	Equal sex ratio	21–25	12 h	Yes	Yes	Yes	Yes	Yes
Veldhuizen *et al.* (2010)	11–20	More females	21–25	Unknown	Yes	No	No	No	No
Eldeghaidy *et al.* (2011)	11–20	More males	26–30	2 h	Yes	No	No	No	No
Nakamura *et al.* (2011)	11–20	Equal sex ratio	21–25	3 h	No	No	No	Yes	Yes
Cerf-Ducastel *et al.* (2012)	11–20	Equal sex ratio	21–25	12 h	Yes	Yes	Yes	Yes	Yes
Green and Murphy (2012)	11–20	More females	21–25	12 h	Yes	No	No	No	No
Nakamura *et al.* (2012)	11–20	Equal sex ratio	21–25	2 h	Yes	No	No	No	No
Green *et al.* (2013)	21–30	Equal sex ratio	36–40	12 h	Yes	No	Yes	No	No
Avery *et al.* (2015)	11–20	More males	26–30	Unknown	Yes	No	No	No	No

The references in the study column of Table 1 are available in ref. 10.

The first set of data was based on demographic data of the 16 studies included in a meta-analysis on neuroimaging studies on human taste perception[10] (see table 1 in ref. 10). The original data presented included sample size, sample sex, sample handedness, sample age (mean and SD), fasting time (time refrained from eating and drinking before the experiment), taste stimuli used, number of brain locations significantly activated, statistical method to correct for multiple comparison, and software used. For simplicity and better visualization, the current illustration included only sample size, sample sex, sample age, fasting time and taste stimuli used. Numerical values were converted to categorical data (binned), and taste stimuli were rearranged into whether each of the five basic tastes was investigated or not.

The second set of data was based on the publication and citation information of 100 studies included in a bibliometric report that identified the 100 most cited neuroscience papers indexed in Web of Science[4] (table 1 of the original paper). The original data presented paper ranking by citation count, publication year, paper title and authors, journal title, normalized citation count, ten-year citation count, total citation count and topic of the papers. The current illustration included the topic of the papers, publication year, ten-year citation count and total citation count only. Except for topic of the papers (which was categorical by itself), the other three variables were converted into categorical data (binned).

Data was compiled into an Excel spreadsheet with each variable represented by a column whereas each included study was represented by a row. The data was then imported into RAWGraphs (http://app.rawgraphs.io/) that generates alluvial diagrams.

The alluvial diagram for the first data set contains nine columns (Figure 1). Most of the 16 included studies had 11–20 participants ($n = 12$). The studies were either had equal sex ratio ($n = 7$) or female predominance ($n = 6$). Half of the studies had participants who were predominantly right-handed, whereas the other half did not report handedness. More than half of the studies had participants with a mean age of around 21–25 years ($n = 9$) and did not report fasting time before the experiment ($n = 9$). These data are also rearranged in Table 1 for readers' comparison with Figure 1.

The alluvial diagram for the second data set contains four columns (Figure 2). Most of the 100 included studies are related to topics 1 ($n = 33$), 5 ($n = 25$) or 6 ($n = 22$), and published during the 1990s ($n = 46$) or 2000s ($n = 43$). Ten-year citation count and total citation count do not seem to relate to each other, as indicated by the presence of both upward and downward flows (purple lines). These data are also rearranged in Table 2 for comparison with Figure 2.

Well-designed graphs have an advantage over tabular data by being more eye-catching but less complex. Infographics are one of the more popular ways to visualize data especially in news media for readers to quickly grasp the essence[11]. Surely infographics are less common in scientific literature because of their artistic rather than scientific nature. As an alternative to presenting data in a tabular form, displaying data with figures intuitively allows readers to summarize more quickly. A disadvantage is that the exact values are often averaged out or hidden during data visualization.

In the current paper, two examples were used to generate alluvial diagrams that summarized the demographic and citation data from respective studies. Compared to the tabular form of the data that consisted of tens or even hundreds of rows, the alluvial diagram showed simplicity. Moreover, the data pattern or relationship between

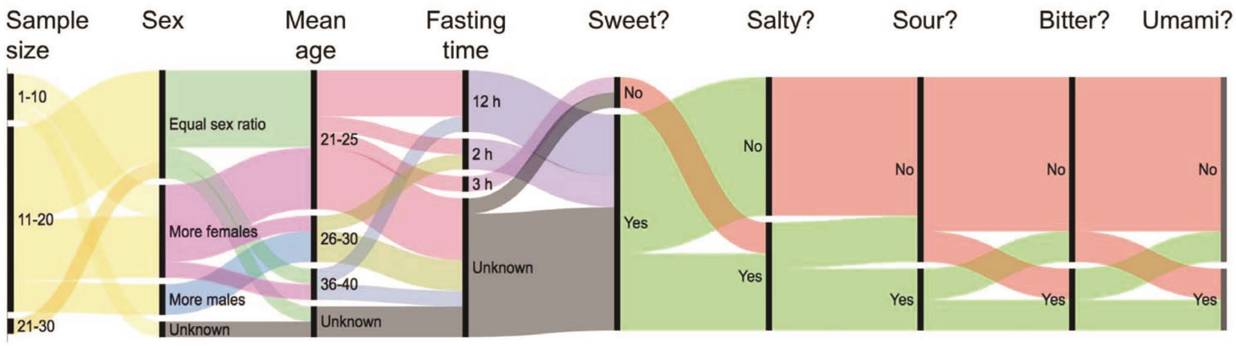

Figure 1. Alluvial diagram summarizing the demographic data from studies included in a meta-analysis. There were 16 studies included in a meta-analysis[10]. While the original study presented these data in a table, readers may take time to digest the data in each column and find out if there existed any patterns between successive data columns. With the alluvial diagram, data is categorized in each column and the ratios of the categories are visualized. Moreover, the relationship between adjacent columns can be visualized easily. For instance, the figure shows that the larger studies with more than 20 participants were all recruiting participants in equal sex ratio, and the studies with male predominance were recruiting participants with a mean age between 26 and 30.

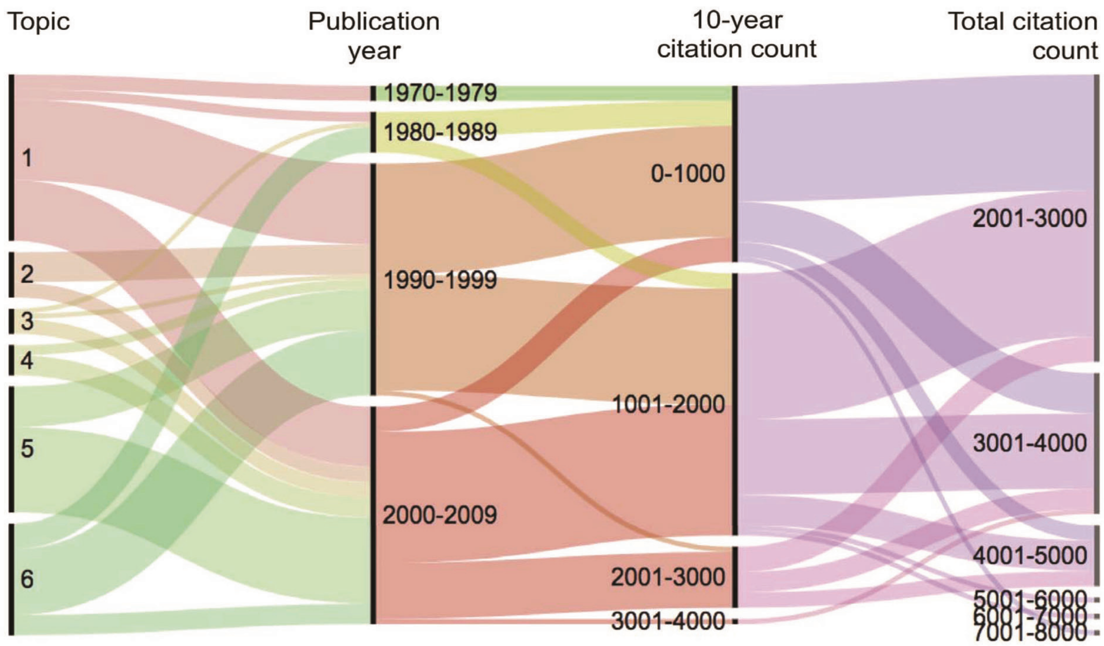

Figure 2. Alluvial diagram summarizing the background data from studies included in a bibliometric report. There were 100 studies included in a bibliometric report[4]. From the diagram it could be easily observed that the papers published in the earlier days focused on topics 1, 3 and 6 only. In particular, papers published during the 1970s were all related to topic 1. Meanwhile, it seems that a high 10-year citation count did not guarantee a high total citation count. For instance, all papers with more than 5000 total citations had only 2000 or less 10-year citations.

successive data columns could be visualized by examining the flows between the columns. Authors can sequence the columns according to their interests, to visualize the relevant relationships, which may be further accompanied by statistical tests such as correlation or chi-squared tests, if deemed suitable.

Compared to other visualization methods such as correlation matrix and network charts, alluvial diagram has certain strengths. For instance, it visualizes the ratios of various items within each categorical variable in an intuitive way, whereas correlation matrix gives numbers or colours based on correlation coefficients but no ratio. Meanwhile, network charts that spread out in multiple directions, make it easy to trace each path but difficult to see and compare ratios. On the other hand, one weakness of alluvial diagram is that there is no specific statistical test for the flow patterns, unlike correlation matrix that specifically presents results from correlation tests. Also, alluvial diagram is 'memory-less' between nodes, meaning that one cannot trace a particular single data point from the beginning column to the last column; so it is more commonly used for displaying relationships between two outcome variables in neuroscience studies in the past[12]. Based on these considerations as well as the

Table 2. Background data from 100 studies included in a bibliometric report compiled in excel spreadsheet for generation of an alluvial diagram

Paper (rank A)	Year (decade)	10-year citation count (binned)	Total citation count (binned)	Topic
1	1980–1989	1001–2000	3001–4000	6
2	1980–1989	1001–2000	3001–4000	6
3	1980–1989	1001–2000	2001–3000	6
4	1980–1989	0–1000	2001–3000	1
5	1970–1979	0–1000	2001–3000	1
6	1990–1999	1001–2000	2001–3000	2
7	1990–1999	1001–2000	2001–3000	6
8	2000–2009	2001–3000	4001–5000	6
9	1990–1999	1001–2000	2001–3000	6
10	1990–1999	1001–2000	2001–3000	6
11	1990–1999	1001–2000	2001–3000	1
12	1970–1979	0–1000	4001–5000	1
13	2000–2009	3001–4000	3001–4000	1
14	1990–1999	1001–2000	4001–5000	1
15	1990–1999	1001–2000	2001–3000	6
16	2000–2009	2001–3000	3001–4000	1
17	1990–1999	1001–2000	2001–3000	5
18	1980–1989	0–1000	3001–4000	6
19	1990–1999	1001–2000	6001–7000	1
20	1990–1999	1001–2000	3001–4000	1
21	2000–2009	1001–2000	3001–4000	4
22	1990–1999	1001–2000	3001–4000	1
23	2000–2009	2001–3000	4001–5000	2
24	2000–2009	2001–3000	2001–3000	3
25	1980–1989	0–1000	2001–3000	6
26	1990–1999	1001–2000	4001–5000	2
27	2000–2009	2001–3000	3001–4000	6
28	2000–2009	2001–3000	4001–5000	4
29	2000–2009	1001–2000	3001–4000	2
30	1990–1999	1001–2000	4001–5000	5
31	1990–1999	1001–2000	2001–3000	2
32	1990–1999	1001–2000	2001–3000	6
33	1990–1999	1001–2000	2001–3000	1
34	2000–2009	1001–2000	3001–4000	5
35	1980–1989	0–1000	2001–3000	3
36	2000–2009	1001–2000	2001–3000	6
37	2000–2009	2001–3000	2001–3000	1
38	2000–2009	1001–2000	4001–5000	5
39	1990–1999	1001–2000	4001–5000	1
40	1990–1999	1001–2000	2001–3000	6
41	2000–2009	2001–3000	3001–4000	3
42	2000–2009	2001–3000	3001–4000	5
43	1990–1999	1001–2000	3001–4000	6
44	2000–2009	1001–2000	5001–6000	5
45	2000–2009	1001–2000	3001–4000	1
46	2000–2009	1001–2000	2001–3000	5
47	1990–1999	0–1000	2001–3000	6
48	2000–2009	1001–2000	2001–3000	1
49	2000–2009	0–1000	2001–3000	1
50	2000–2009	1001–2000	3001–4000	4
51	1990–1999	1001–2000	3001–4000	5
52	2000–2009	1001–2000	2001–3000	4
53	1990–1999	1001–2000	2001–3000	6
54	2000–2009	1001–2000	3001–4000	5
55	1990–1999	0–1000	2001–3000	1
56	2000–2009	1001–2000	2001–3000	2
57	2000–2009	2001–3000	2001–3000	1
58	1990–1999	1001–2000	3001–4000	4
59	2000–2009	2001–3000	2001–3000	5

(*Contd*)

Table 2. (*Contd*)

Paper (rank A)	Year (decade)	10-year citation count (binned)	Total citation count (binned)	Topic
60	2000–2009	1001–2000	4001–5000	3
61	2000–2009	1001–2000	2001–3000	5
62	2000–2009	1001–2000	2001–3000	5
63	2000–2009	1001–2000	2001–3000	6
64	1970–1979	0–1000	2001–3000	1
65	1990–1999	1001–2000	2001–3000	6
66	2000–2009	1001–2000	2001–3000	1
67	2000–2009	1001–2000	2001–3000	1
68	2000–2009	1001–2000	2001–3000	1
69	1990–1999	0–1000	4001–5000	1
70	2000–2009	1001–2000	2001–3000	1
71	2000–2009	1001–2000	3001–4000	5
72	2000–2009	1001–2000	2001–3000	1
73	2000–2009	1001–2000	2001–3000	5
74	1990–1999	0–1000	3001–4000	6
75	2000–2009	1001–2000	2001–3000	5
76	1980–1989	0–1000	7001–8000	1
77	1990–1999	0–1000	2001–3000	1
78	1990–1999	0–1000	3001–4000	1
79	1990–1999	0–1000	2001–3000	1
80	1990–1999	0–1000	3001–4000	2
81	2000–2009	1001–2000	3001–4000	5
82	1990–1999	0–1000	2001–3000	1
83	1990–1999	0–1000	4001–5000	5
84	1990–1999	0–1000	2001–3000	2
85	2000–2009	0–1000	2001–3000	5
86	2000–2009	0–1000	2001–3000	5
87	1990–1999	0–1000	3001–4000	1
88	2000–2009	0–1000	2001–3000	5
89	1990–1999	0–1000	2001–3000	1
90	1990–1999	0–1000	2001–3000	5
91	2000–2009	0–1000	2001–3000	5
92	1990–1999	0–1000	2001–3000	4
93	1990–1999	0–1000	2001–3000	6
94	1990–1999	0–1000	2001–3000	5
95	1990–1999	0–1000	2001–3000	5
96	1990–1999	2001–3000	2001–3000	6
97	1990–1999	0–1000	3001–4000	1
98	1990–1999	0–1000	3001–4000	5
99	1990–1999	0–1000	2001–3000	2
100	1990–1999	0–1000	3001–4000	3

Please refer to the original paper[4] for the meaning of Rank A and the coding of topics.

visualization examples in the current paper, it is recommended that alluvial diagrams are good for displaying the background demographic factors of a study if each categorical variable has limited classes (e.g. 6–8 classes; otherwise consider regrouping the data using fewer 'bins' or class intervals).

The modern scientific literature is growing fast, and it is often challenging for readers to quickly identify the papers relevant to one's own interests and to understand the implications from summarizing reports such as meta-analyses. Together with other research reports such as those focusing on analysis of cited references[13–16] and those surveying journal editorial practices[17,18], the literature review could be much more comprehensive. The usage of alluvial diagrams for summarizing purposes may help readers comprehend better. Also its application should be versatile.

The current study illustrated the usefulness of an alluvial diagram in displaying data from bibliometric report and meta-analysis. It showed that alluvial diagram does not only apply to temporal changes of network data, but also functions as a tool to help readers visualize summarized data for better comprehension of existing literature.

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Prevalence and risk factors of hypertension among Mizo population: a population-based epidemiological study from North East India

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The aim of the present study was to assess the prevalence and risk factors of hypertension (HTN) in the Mizo population from Mizoram, North East India. We carried out a cross-sectional study among urban and rural populations. Socio-demographic and clinical information, including blood pressure and anthropometric measurements were collected by house-to-house visits and recorded in a predesigned and pretested questionnaire. The study included a total of 12,313 subjects (male: 5707, female: 6606) from urban (n = 5853) and rural (n = 6460) localities. All information was analysed using the statistical package SPSS-17. Prevalence of HTN was 15.9% with significant urban–rural (18.9% versus 13.2%, $P < 0.001$) and gender variation (18.2% versus 13.9%, $P < 0.001$). Logistic regression analysis in the overall (rural and urban) model was carried out, which revealed that age, extra salt (salt as a side dish), tuibur (a special form of tobacco), high BMI and sedentary lifestyle were independently associated with HTN ($P < 0.05$). This study has public health implications, as community-based lifestyle intervention of these risk factors may alleviate the burden of HTN.

Keywords: Dietary salt, epidemiological study, hypertension, prevalence and risk factors.

HYPERTENSION (HTN) now seems to contribute significantly to the global burden of several non-communicable diseases and mortality[1]. It has been reported that HTN contributes to the highest percentage of attributable death (~13) and is the foremost cause of disability accounting for more than 4.4% of global disability-adjusted life years (DALYs) in middle-aged and old-aged people[2]. India is undergoing a rapid economic growth with changes in demographic and cultural norms, and lifestyle-related behaviours which have had a large impact on the health profile and epidemiological transition. This shift or transition may be associated with the emergence of

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