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A study of the online prominence and sentiment of the top 100 global brands

About the Author

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David has almost 20 years' experience in the online brand-protection industry, serving clients across a range of sectors and industries. He started his career at Envisional in 2004, subsequently moving to NetNames (2007) and then CSC (2016). Since July 2023, David has been working as Brand Protection Strategist at Stobbs. He is an experienced thought leader, with an extensive portfolio of articles and experience of speaking at industry events, and is author of 'Brand Protection in the Online World' (2016).

Contents

Executive Summary

- In this study, we present a new methodology for measuring the online prominence and sentiment of a group of brands, and apply the approach to the top 100 most valuable global brands in 2023. The metrics are likely to be linked to factors associated with search-engine optimisation, web traffic, brand valuation, and customer perception, but can be produced using a much more simplified and scalable approach.

- The analysis is based on a dataset of over 4,300 of the most highly-ranked webpages returned by google.com in response to searches for a set of 50 generic business-related keywords.

- The measurement of brand prominence is built on the concept of a ‘brand content score’, a metric representing the degree to which a webpage can be considered to be ‘about’ a brand (or other keyword) of interest, considering both the number of mentions and the prominence of those individual mentions on the page.

- The measurement of sentiment is carried out by considering the proximity of the brand mentions to any of a pre-defined library of positive and negative sentiment keywords.

- Google was found to be the most prominent brand by a significant margin; the top five brands (and their prominence scores) are: Google (2.856), Microsoft (0.670), LinkedIn (0.655), Amazon (0.637) and Facebook (0.523).

- There is a positive (though relatively weak) correlation between online brand prominence and brand value, with three of the top four most prominent brands (Google, Microsoft and Amazon) appearing in the top four of the Kantar brand value index. However, the Kantar list also reflects other brand factors relating to the ability to generate revenue, so it is perhaps not surprising that the overall correlation is not stronger.

- The group of brands which are disproportionately more prominent than would be expected by virtue of their brand value is dominated by those in the social-media and search sectors (Google, Facebook, LinkedIn, Instagram and YouTube) and the technology sector (Oracle, Salesforce and SAP), reflecting both their general overall online prominence and the frequency of their mentions in web content relating specifically to business.

- Certain luxury brands (Louis Vuitton, Hermes, Chanel) are notable for their relative low prominence in the dataset of webpages considered, perhaps reflective of their lower reliance on search-engine optimisation, and increased reliance on brand reputation, to drive users to their online content.

- Considering also a set of large Internet and/or social-media brands which do not feature in the overall list of top 100 most valuable brands, Twitter / X was found to be the most prominent. Overall, it appears in fifth place (between Amazon and Facebook) when ranked within the main list of brands.

- The top five brands in the dataset by online sentiment are: Amazon (22.48), Microsoft (21.47), Google (20.81), Facebook (13.67), and Apple (13.48). The top four most valuable brands overall all appear in this top five. The most negatively referenced brand overall is ICBC (-2.71), in part due to references to the recent cyber-attack against the organisation.

- Future applications of this analysis might involve consideration of more focused sets of brands, potentially using industry- or product-related search terms and/or specific channels of interest, to gain a deeper dive into content areas such as customer comment. Use of a consistent approach in any given study will also allow trends over time to be tracked, thereby allowing analysis of the impact of marketing initiatives, product launches or news stories.

- Areas for development might include the use of more comprehensive keyword-based filtering keywords to exclude generic references to brand terms, ‘tuning’ of the sentiment keyword libraries to better suit specific areas of content, more in-depth analysis to separate ‘official’ brand references from ‘unauthorised’ use, and the use of region-specific searches and local-language search and matching terms, to better sample content relating to international brands.

Study overview and methodology

Introduction

The online prominence of brands can be a key metric for brand owners, and can serve as a data input for a number of areas, including search-engine optimisation and web-traffic analysis, and brand valuation. Overall, it provides a measure of the amount of accessible brand-related online content – both official and third-party – and can also provide an indication of the likelihood of a brand being targeted by infringers. The sentiment associated with brand mentions is also of key significance, providing information relating to customer perception and brand value, and allowing factors such as the impact of news stories and marketing initiatives to be tracked.

In this study, we present the results of an analysis of the online prominence and sentiment of the top 100 most valuable global brands in 2023[1] (Appendix A), using newly-developed metrics. The methodology for measuring brand prominence is essentially identical to that used in an initial proof-of-concept study of the top twenty fashion brands[2].

[1] https://www.kantar.com/inspiration/brands/revealed-the-worlds-most-valuable-brands-of-2023
[2] https://www.iamstobbs.com/measuring-brand-prominence-of-fashion-brands-ebook

Methodology

1. Brand prominence

The basic principle behind the methodology to measure online brand prominence is to obtain a representative sample of webpages of potential relevance (e.g. to the business area of the brands concerned) and then determine the number and prominence of mentions of each of the brands of interest on each webpage, across the dataset.

One of the main points to note in this type of analysis is that it is necessary not to explicitly search for any of the brand names in question. The reason for this is that – by definition – for any given query submitted to a search engine, all of the results will relate to the search term being used. Even if the analysis considers all such results, by continuing to paginate through until no further results are returned, this will usually only return a maximum number of results (typically a few hundred) for any given search engine and query. If, therefore, we simply search for each brand name separately, this will yield a relatively consistent number of results for each brand, and the brands will artificially appear to have similar online prominences. Instead, it is preferable to use generic search queries to bring back sets of pages relevant to the industry area of the brands in question (or to business in general) and count the mentions of the brands (and measure their prominence in each case) which happen to appear in this overall representative sample of pages.

In this analysis, we consider the content of a set of webpages returned in response to searches on google.com for each of 50 keywords related

generally to business ('business', 'company', 'employer', 'industry', 'profits', 'revenue', etc.), considering the first page of (approximately 100) results in each case. The list of links was then de-duplicated, to retain the unique URLs, of which there were 4,376[3].

The next stage is, for each of the 100 brands under consideration, to measure the number and prominence of the mentions of the brand on each of the pages in the dataset. In general, prominence is determined by the type of context in which the brand is mentioned (e.g. in the URL vs. the page title vs. a level-1 or level-2 heading vs. any other mention on the page); this analysis is carried out by considering the full content of the HTML source-code of the webpage.

Brand mentions are identified by matching the content of the webpage HTML using 'regular expressions' ('Regex'), a formulation which allows wildcard-based searching and is able to identify brand references within longer strings (such as the URL of the page). However, because this approach is taken, it was necessary to construct the match-terms in such a way so as to avoid non-relevant false positives in cases where the brand names could appear within longer acronyms or as sub-strings within longer words (e.g. for 'Chase', we wish to exclude terms such as 'purchase'). In order to do so, for brand names where this may be an issue, we match only for brand appearances where they are preceded / followed by characters other than letters. Where appropriate, brand variations were also included in the matching (e.g. for 'TCS' (Tata Consultancy Services) we also consider

[3] Findings are based on results returned and analysis of live webpage content as of 14-Nov-2023

references to ‘tata.?consult.*’, where ‘.?’ is any optional one character and ‘.*’ is any number of characters). Similarly, for the most generic brand names, the matching terms were modified in order to require a specific additional qualifying term (as is usually used in conjunction with the brand name) to be present, to minimise false positives. The brands modified in this way were:

- For TD, the matching term was modified to require the webpage to reference ‘td.?bank’ (where ‘.?’ is an optional character) specifically, in order for a brand reference to be deemed to have been identified

- For JD, the matching term was modified to require the webpage to reference ‘jd.?com’ (or ‘jingdong’) specifically

These changes will mean that some relevant mentions (referencing just ‘TD’ or ‘JD’) may be missed, but are intended to provide an overall more realistic reflection of the amount of brand-relevant content.

In earlier formulations of similar methodologies[4,5,6], the subsequent analysis was carried out simply by considering the numbers of pages on which there was at least one brand mention in each of the key areas of content (URL, title,

[4] https://www.businessweekly.co.uk/news/hi-tech/9121-online-research-gives-insight-damage-banks-brands
[5] https://www.trademarksandbrandsonline.com/news/luxury-brands-not-doing-enough-to-protect-themselves-online-4482 (cache available at https://webcache.googleusercontent.com/search?q=cache:9oyINc1E1AwJ:https://www.trademarksandbrandsonline.com/news/luxury-brands-not-doing-enough-to-protect-themselves-online-4482&sca_esv=580550388)
[6] ‘The Digital Brand Risk Index: A NetNames Report’; PDF available at https://silo.tips/download/the-digital-brand-risk-index-a-netnames-report

etc,) on the page. However, this approach is somewhat unsatisfactory, as it fails to distinguish (for example) a page which mentions a brand once in its page title from one featuring multiple mentions in the title (and, correspondingly, actually has a greater degree of 'brand-related' content). In this study, we present an improved methodology, utilising the concept of a 'brand content score' for each brand on each page.

Brand content score

The brand content score (which can be calculated for a specific brand or keyword on any given webpage) is a useful metric in its own right, with general applications in a range of areas.

Its calculation involves counting each mention of the brand on the page, and weighting each one according to its prominence - e.g. a mention in the URL 'scores' more highly than a mention in the page title, which scores more highly than a mention in a level-1 heading, and so on. In our formulation, we also have the option to 'cap' the contribution to the total score from each specific area, to avoid skewing the results by 'junk' pages which may be 'stuffed' with very large numbers of mentions of random terms.

The range of scores obtained by this analysis will be dependent on the relative weightings and data caps used, as well as the types of search queries used to generate the results and the keywords being matched.

In brand monitoring, brand content score can also be used as a basis for prioritising results – for example, when large numbers of webpages are

identified using a monitoring tool. Those pages assigned the highest scores – i.e. those of greatest potential relevance to the brand in question - are typically the primary targets for further analysis, may be priorities for further monitoring (e.g. content tracking) and enforcement, and can provide insight into keywords and TLDs (domain extensions) most used in relevant content, which can help inform domain registration policies[7,8].

In this analysis, we calculate the brand content score for each brand under consideration, for each webpage in the dataset, and use the mean value across all pages for each brand as the basis for the comparison of the relative online prominence of the 100 brands.

In some cases, analysis of the page will not be possible (e.g. if the page returns an HTTP status code deemed to be an error code).

2. Brand sentiment

For each identified mention of any of the brands under consideration on each webpage, we also calculate a sentiment score, indicating the 'sense' of the references ('positive' or 'negative'). The basic formulation is as follows:

- For each webpage under consideration, the overall sentiment score for each brand is based on the proximity of each mention of the brand to any of a library of 'positive'[9] or 'negative'[10] keywords[11].

[7] 'Technical aspects of brand monitoring', internal Stobbs training presentation
[8] https://www.iamstobbs.com/opinion/strategies-for-constructing-a-domain-name-registration-and-management-policy

- In this simplest formulation, all keywords are deemed to be of equal ‘strength’, and the score assigned to each instance of a sentiment keyword near to a brand mention is determined according to just their proximity, using an exponentially decaying function (so that instances where the pair of words appear more closely together will be assigned a higher score) (Appendix B). The maximum score (assigned where the words appear adjacently on the webpage – i.e. a proximity of 1 word) and the rate of decay of the score with increasing proximity (the ‘proximity half-life’) can both be chosen. In this study, we use a maximum score of 100 and a proximity half-life of 1 word.

- For each mention of each brand on a webpage, the nearby words (up to a maximum proximity; the distance at which the proximity score drops to zero) are inspected, to determine if any of these are sentiment keywords from the keyword library. If so, the proximity score is calculated according to the distance between the two words. If the keyword is positive, the appearance will be assigned as a positive score component, and vice versa. The total positive and negative scores for each brand can then be calculated, and the overall sentiment score for the brand on the page in question is the difference between the two (i.e. overall sentiment score = positive sentiment score – negative sentiment score). An illustration of how this technique works in practice is shown in Appendix C.

[9] https://ptrckprry.com/course/ssd/data/positive-words.txt
[10] https://ptrckprry.com/course/ssd/data/negative-words.txt
[11] Minqing Hu and Bing Liu. ‘Mining and Summarizing Customer Reviews‘, Proceedings of the ACM SIGKDD International Conference on Knowledge Discovery and Data Mining (KDD-2004), Aug 22-25, 2004, Seattle, Washington, USA.

The following details relating to the specifics of the analysis may be noted:

- The text-content of the page is ‘cleaned’ by removing any line-breaks, tabs or other punctuation symbols (- ‘ “ , . ; : & * ( ) @ # /) and any instances of multiple consecutive spaces. The remaining content of the page is split into a list of words, for analysis.

- A brand- or keyword mention is deemed to have been identified only if it is an exact mention. This requires each brand name (and keyword) to be represented as a single string (word) with no punctuation characters, and any variant brand references on the page to be replaced with the brand name in the same format prior to analysis (e.g. “coca-cola” and “coca cola” are replaced with “cocacola”). The same approach can be taken with other brand references deemed to pertain to the brand in question (e.g. “lvmh” is replaced with “louisvuitton”).

- It was also necessary to make the following modifications to the lists of keywords:

    - The following terms were removed from the library of negative keywords*:

        - ‘cloud’ – this term is referenced frequently in relation to IT, and would otherwise skew the results, particularly for brands such as Google, Oracle, Shell (where the term can be used in reference to its software definition), etc.

* For more robust future studies, it may be necessary to carry out a more detailed edit of the keyword lists and/or to create bespoke lists for particular industries or business areas.

        - ‘sap’ – this term is indistinguishable from the SAP brand name, and would otherwise mean that every mention of SAP would be (by definition) in immediate proximity (separation zero) with a negative keyword, such that it would not be possible to get a meaningful sentiment measure for this brand.

        - ‘limited’ – this term occurs frequently as a neutral keyword in a business-related context (as part of company names, etc.).

- The following other modifications were also made, to prevent brand confusion / false positives:

    - Explicit references to ‘start(-)ups’ and ‘ups(-)and(-)downs’ were removed from all webpage content prior to analysis, to prevent confusion with the UPS brand.

- The most straightforward formulation of the overall sentiment score for each brand would then be to calculate it as the mean of the sentiment scores on all pages on which a reference to that brand was identified. However, this approach raises the possibility that the score could be affected by a small number of ‘outliers’ with extreme scores (as might arise from false-positive brand references or ‘junk’ pages ‘stuffed’ with large numbers of keywords). Accordingly, we adopt the same approach as used in previous similar studies[12], namely:

[12] http://news.bbc.co.uk/1/hi/technology/4468745.stm

- Before calculating the mean across all pages, the cube root is taken of the raw overall sentiment scores for each brand on each page, to reduce the impact of outliers.

- The average sentiment score is then multiplied by the square root of the number of contributing webpages. This provides a measure of significance, and upweights the score for brands where the mentions are consistently positive or negative, and downweights it for brands for which the scores would otherwise be ‘skewed’ due to the fact that only a few relevant pages had been identified.

Findings

1. Brand prominence

The overall prominence scores for the brands (calculated as the mean of the brand content scores across all webpages in the dataset) are shown in Figure 1 and Appendix D.

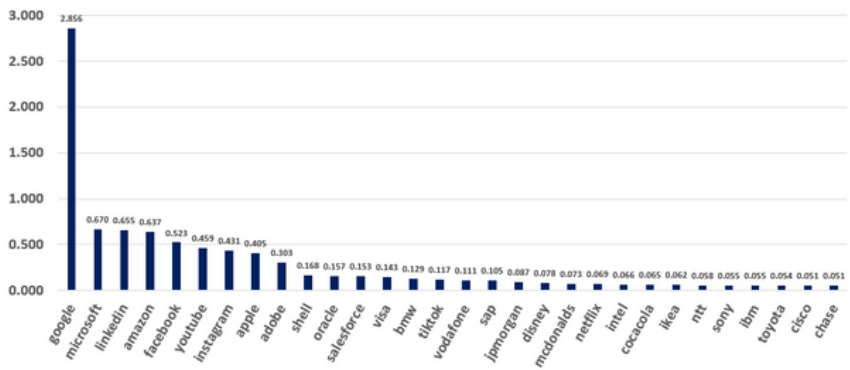


Figure 1: Overall prominence scores for the top thirty most prominent brands (out of the set of 100 most valuable brands)

Figure 2 shows a comparison between the overall prominence score and the ranking in the Kantar list of most valuable brands, for each of the top thirty most prominent brands.

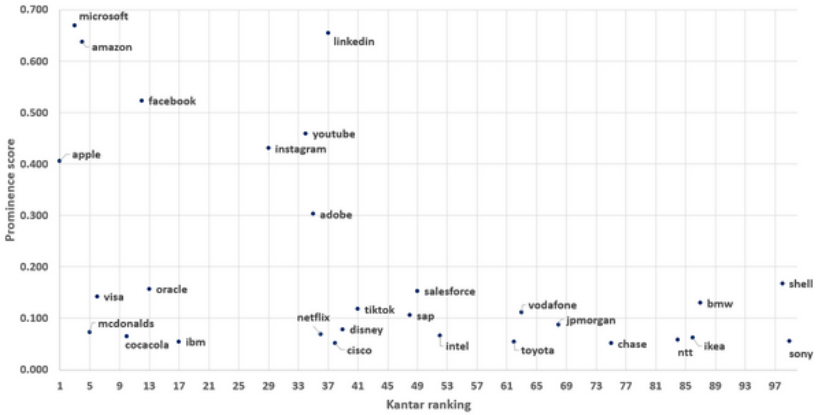


Figure 2: Comparison of overall prominence score with Kantar ranking, for the top thirty most prominent brands (excluding Google)

Overall, Google is the most prominent brand within the set of webpages considered, by a significant margin, followed by Microsoft, LinkedIn, Amazon and Facebook. There is also a weak correlation between the ranking of the brands (according to the Kantar index) and their prominence scores, with many of the more highly ranked brands having higher prominences. For example, three of the top four most prominent brands (Google, Microsoft and Amazon) appear in the top four of the Kantar index.

Note that the ordering of the brands is different from that where we consider only the total number of pages within the dataset on which a brand mention was identified (Table 1), since the prominence score also takes account of the type of location on the page (i.e. URL, page title, heading, etc.) on which the mentions appear.

Brand term	No. pages
facebook	1,001
linkedin	843
youtube	794
instagram	619
google	476
amazon	238
apple	206
microsoft	171
tiktok	110
ups	85

Table 1: Numbers of pages within the dataset on which at least one brand mention was identified, for the top ten most commonly appearing brands

The distribution of brand content page scores, for each of the top five most prominent brands overall, is shown in Figure 3. Overall, the general principle is that the brands with the greatest prominence appear in general on more of the webpages within the dataset, and have greater numbers of pages giving higher brand content scores.

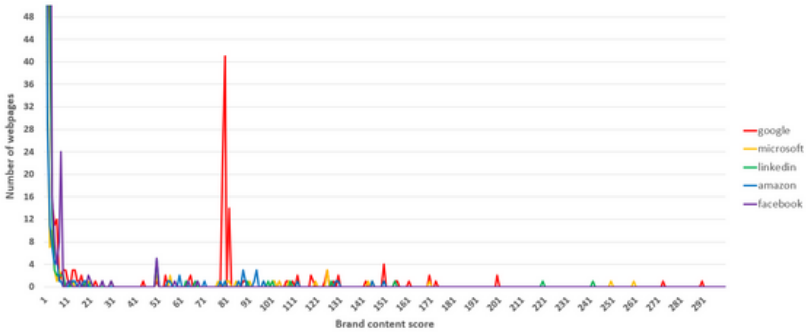


Figure 3: Distribution of brand content page scores, for each of the top five most prominent brands

It is also informative to consider the most highly scored webpages within the dataset, according to individual brand content scores, as shown below.

Top three pages in the dataset, by highest individual brand content score:

- https://about.google/belonging/at-work/
  - (brand term: google; score 290)
- https://github.com/googleapis/google-api-python-client
  - (brand term: google; score 273)
- https://www.immigration.govt.nz/new-zealand-visas/visas/visa/samoan-quota-scheme-resident-visa
  - (brand term: visa; score 272)

The top page in the dataset is from an official Google website, which (unsurprisingly) achieves the highest score in terms of the degree to which the content pertains to the Google brand. However, just the presence of an official site in the dataset (returned in response to a generic search query) is significant, giving an indication of the strength

of the brand owner's search-engine optimisation strategies.

The third-placed page in the above list is noteworthy because it raises an interesting question about the handling of 'false positives'; the page features numerous prominent references to 'visa', but this is generally in the context of immigration visas, rather than in reference to the credit-card brand. Similar comments will also apply to some of the references of many of the other brands, particularly where the brand name is a generic term (such as 'shell', 'chase' or 'ups') or can appear in other contexts, including usage by other brand owners (e.g. 'bca' (intended to refer to Bank Central Asia) can also pertain to 'British Car Auctions', 'BCA Leisure', etc.). This is potentially the reason why some of these brands are quite so highly ranked. In more sophisticated formulations of the methodology, these 'false positives' could be accounted for (to a degree) via the use of 'positive' (relevance) or 'negative' (exclusion) keywords. However, because of the very large numbers of possible such permutations, and the desire to treat all brands equally (as far as possible), no further 'corrections' along these lines have been applied in this study. Arguably, the fact that the overall scores reflect both 'legitimate' brand references and 'other' uses of the brand term does provide useful information on the extent to which the brand name is used online – which relates to issues such as brand distinctiveness and brand dilution. Any attempt to separate these two types of brand reference would require a much more in-depth analysis.

Considering next a deeper dive into the prominence data, we consider the correlation between prominence score and absolute brand value as given by the Kantar analysis (rather than just the relative rankings), and also split the brands by industry area to determine whether any of the trends are sector-specific.

In the original analysis by Kantar, the 100 brands are assigned into 18 different business categories; in our analysis, we adopt a simplified approach utilising 11 different industry areas. These are listed below, together with the Kantar categories to which they correspond (for the cases where more than one category is included or a different descriptor is used).

- Retail
- Alcohol, food and tobacco
  - Alcohol
  - Tobacco
  - Food and beverages
  - Fast food
- Apparel and luxury
  - Apparel
  - Luxury
- Personal care
- Financial services
- Media and entertainment
- Logistics
- Automotive
- Technology
  - Business technology and services platforms
  - Consumer technology and services platforms
  - Conglomerate (Siemens)
  - IoT ecosystem (Haier)
- Telecommunications
  - Telecom providers
- Energy

The findings are shown in Figures 4 and 5.

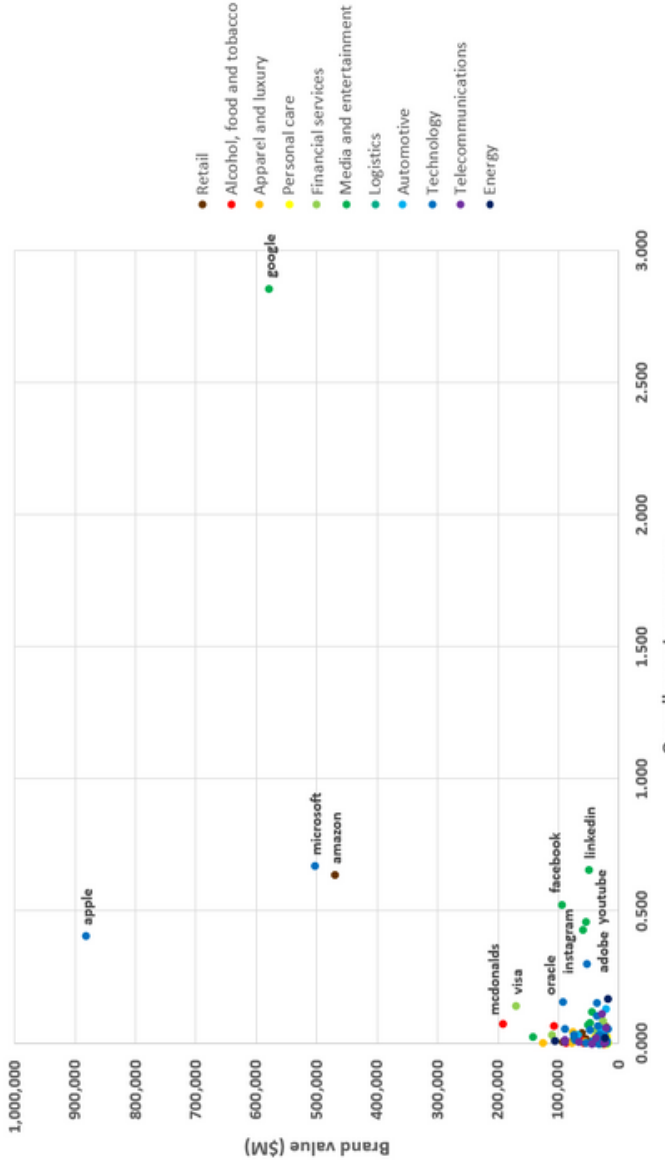


Figure 4: Comparison of overall prominence score with brand value, for the top 100 brands, split by industry area

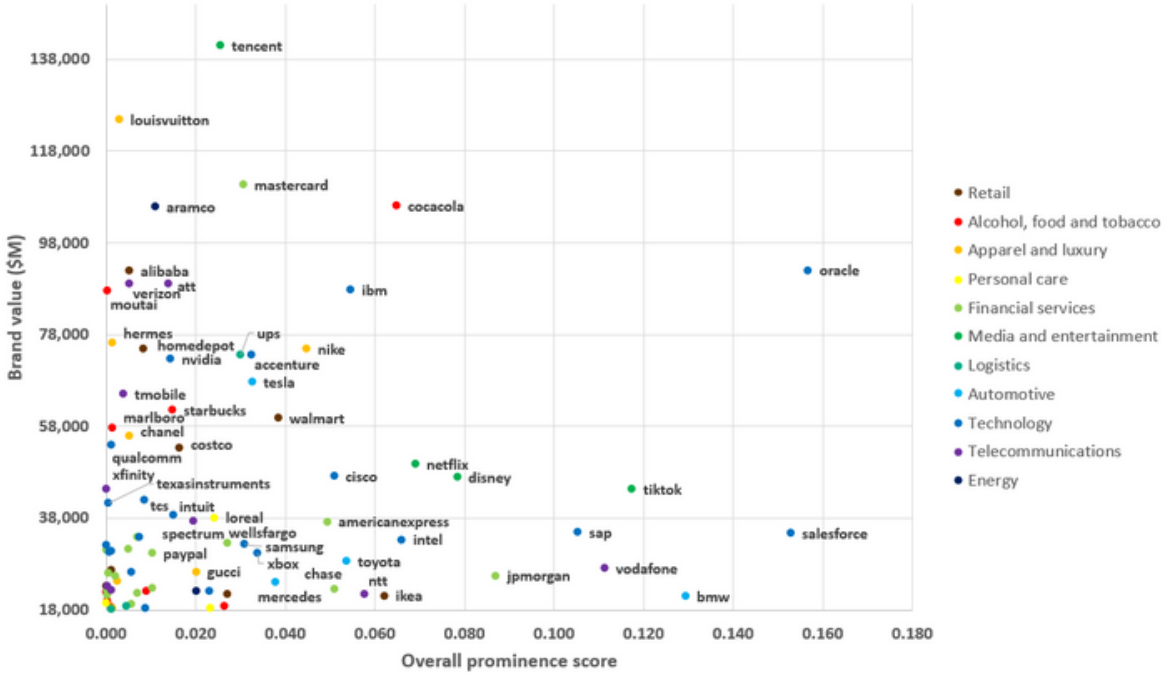


Figure 5: Comparison of overall prominence score with brand value, for the top 100 brands, split by industry area (detailed zoom)

Overall, there is a general positive (though relatively weak) correlation between brand value and our determination of prominence score (overall correlation coefficient = +0.61),

In addition, the following top-level trends are evident:

- Brands which are disproportionately more prominent than would be expected by virtue of their brand value (i.e. those appearing towards the bottom-right of the graphs) are dominated by those in the media and entertainment sector (especially the social-media and search brands Google, Facebook, LinkedIn, Instagram and YouTube) and the technology sector (specifically Oracle, Salesforce and SAP). These observations are likely to be reflective of the ubiquitous nature of the former set of brands, and the frequency with which the latter set of business-service brands are referenced in general business-related content.

- The set of brands which are disproportionately less prominent than would be expected by virtue of their brand value (i.e. those appearing towards the top-left of the graphs) is more varied, but it is notable that many of the luxury brands (Louis Vuitton, Hermes, Chanel) appear in this area. This may be reflective of both the high value of these brands generally, and the extent to which they perhaps need to be less reliant on search-engine optimisation techniques, relying instead on reputation to drive traffic to their online content.

It is also informative to compare the online prominence of these top 100 brands with that of a selection of other brands which are likely to have significant online presences, but do not appear in the list of most valuable brands. In order to do so, we consider a set of 15 of the largest Internet and/or social media brands[13,14,15,16] which do not appear in the list of 100 most valuable brands overall (Appendix E). The same set of 4,376 webpages was then analysed identically as described above, to determine the overall prominence scores of these additional brands[17].

The overall prominence scores for the additional brands are shown in Table 2, which also includes the top ten brands from the main study, for comparison.

Table 2 (next page): Overall prominence scores for the additional large Internet and/or social-media brands (with the top ten brands from the main study shown in red)

[13] https://www.investopedia.com/articles/personal-finance/030415/worlds-top-10-internet-companies.asp
[14] https://www.statista.com/statistics/209331/largest-us-internet-companies-by-market-cap/
[15] https://en.wikipedia.org/wiki/List_of_largest_Internet_companies
[16] https://www.statista.com/statistics/272014/global-social-networks-ranked-by-number-of-users/
[17] Findings from this additional study are based on analysis of live webpage content as of 27-Nov-2023. The analysis was also repeated on this date for the Google brand, which found that its overall prominence score was 2.855 (i.e. within 0.008% of its original value of 2.856) (with appearances on 481 pages in the dataset, cf. 476 previously), consistent with the assertion that there have been only minimal changes to the content of the set of webpages in the intervening two-week period, and that the prominence scores for these additional brands can therefore be compared with those presented above for the top 100 most valuable brands, on a like-for-like basis.

Brand	Prominence score
Google	2.856
Microsoft	0.670
LinkedIn	0.655
Amazon	0.637
Twitter / X	0.524
Facebook	0.523
YouTube	0.459
Instagram	0.431
Apple	0.405
Adobe	0.303
QQ	0.243
Shell	0.168
WhatsApp	0.056
Pinterest	0.042
ServiceNow	0.029
Snapchat	0.008
WeChat	0.003
Telegram	0.003
Booking.com	0.002
Sina Weibo	0.002
Douyin	0.000
Baidu	0.000
Yandex	0.000
Pinduoduo	0.000
Kuaishou	0.000

The number of pages on which at least one mention was identified, for each of these additional 15 brands, is shown in Table 3.

Brand	No. pages
Twitter / X	1,022
Facebook	1,001
LinkedIn	843
YouTube	794
WhatsApp	73
Pinterest	56
QQ	54
Snapchat	20
WeChat	12
ServiceNow	10
Sina Weibo	8
Telegram	7
Booking.com	6
Douyin	1
Baidu	0
Yandex	0
Pinduoduo	0
Kuaishou	0

Table 3: Numbers of pages within the dataset on which at least one brand mention was identified, for the additional large Internet and/or social-media brands (with the top three brands from the main study shown in red)

Amongst the additional 15 brands, Twitter / X (for which the latter variant was identified by searching explicitly for ‘x.com’, to avoid false positives) is noteworthy by having by far the greatest online prominence (actually the only one of the additional brands to appear in the top ten of the overall list), and the greatest ubiquity (in terms of number of pages where a mention was identified), despite not appearing in the list of top 100 most valuable brands overall.

The overall prominence of QQ (the second placed of the additional brands in terms of prominence) is likely to be an over-estimate, due to the generic nature of the brand name, and the potential for false positives. In particular, the string ‘qq’ seems to appear frequently in the source code of webpages displaying PDF files; if these files are excluded from the dataset, the overall prominence score for QQ drops to 0.028.

2. Brand sentiment

The overall sentiment scores for the top 100 brands are shown in Figure 6 and Appendix F.

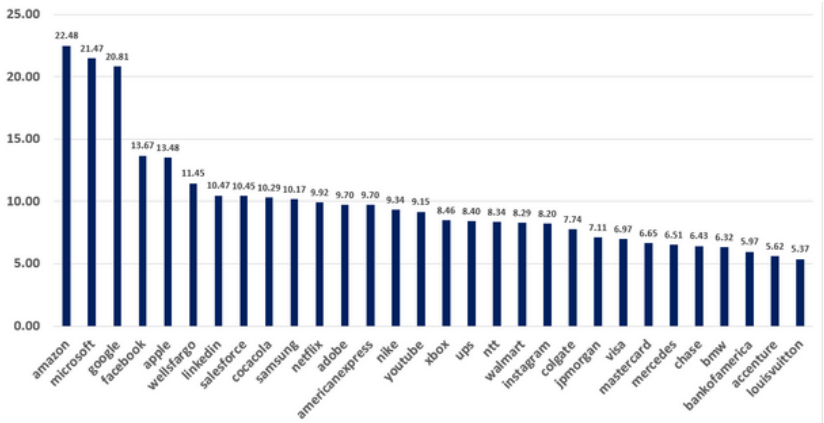


Figure 6: Overall sentiment scores for the top thirty most positively referenced brands (out of the set of 100 most valuable brands)

It is noteworthy that the top four most valuable brands (Apple, Google, Microsoft, Amazon) all appear in the top five brands which are most positively referenced overall, with Amazon achieving the most highly positive sentiment score. Part of the reason for this top ranking is the fact that the dataset actually includes several pages from the official Amazon website, together with other sites which are affiliated with the brand, or provide brand-specific information (such as amazonworkspaces.com and aboutamazon.com). An example of one of the highly-scored pages for Amazon is shown in Figure 7; this page can be seen to feature a reference to the brand in conjunction with positive phraseology, consistent with the assertion that the metric is generating meaningful results.

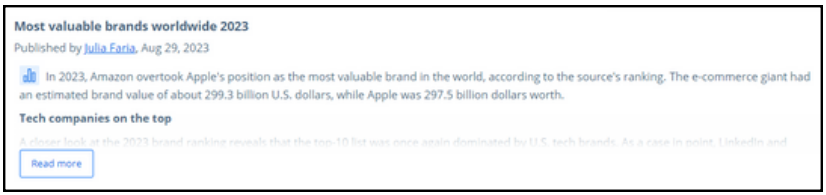


Figure 7: Example of an extract from a webpage including a positive reference to Amazon (sentiment score: +100)

Conversely, the bottom (most negatively referenced) brand in this analysis is ICBC. This appears to be, at least in part, due to to news stories surrounding the recent cyber-attack against the organisation[18] (Figure 8).

Figure 8: Example of an extract from a webpage on which ICBC is negatively referenced (in conjunction with the negative keywords 'hack' and 'disruption') (sentiment score: -56)

[18] https://www.ft.com/content/d3c7259c-0ea6-414b-9013-ac615b1a8177

Discussion and Conclusions

The methodology described in this article represents a simple approach for comparing the online prominence and sentiment of different brands, focusing on the most highly-visible online content (i.e. the webpages appearing near the top of the search-engine rankings). Overall, we might expect online prominence to be associated with factors relating to search-engine optimisation, web traffic, and brand valuation, but to be measurable in a much simpler and more scalable way.

The same approach can also be applied to more comprehensive studies, which could incorporate larger datasets of webpages, potentially drawn from a wider range of search sources targeting different geographical markets, and utilising as many relevant search queries as appropriate. It is noteworthy, for example, that the results from this study are dominated by English-language content, using just the google.com search engine (and are potentially also biased by virtue of running the searches from a UK-based IP address). This will undoubtedly contribute to overseas brands being under-represented in the statistics, which could be mediated in future studies by the use of region-specific search-engines and proxy servers, and the use of local-language search terms and brand matching.

In any study of this type, it is important to deal correctly with brand names which are relatively generic, to ensure that references are considered properly and avoid false positives. In such cases, it may be necessary to make use to keyword-based filtering to distinguish the relevant mentions from

other uses of the brand name. Similarly, it may be appropriate to create bespoke versions of the sentiment keyword lists which are appropriate to specific industry areas.

Furthermore, providing a consistent approach is used for any given series of studies, the methodology also offers the potential for tracking trends and changes over time in relative prominence (without the need to 'normalise' the scores to a consistent baseline, as was the case in some earlier studies)[19,20,21], allowing factors such as the impact of marketing initiatives or news stories to be tracked.

Overall, the analysis of the top 100 most valuable brands gives (based on a sample of webpages related generally to business) the three most prominent as Google, Microsoft and LinkedIn, and the three most positively referenced as Amazon, Microsoft and Google. There is also a general (though relatively weak) positive correlation between brand prominence and brand value (as determined by the Kantar study). The main exceptions to this observation are social-media / search (Google, Facebook, LinkedIn, Instagram and YouTube) and technology (Oracle, Salesforce and SAP) brands, which are disproportionately highly represented in our dataset of sample webpages, and a selection of luxury brands (Louis Vuitton, Hermes, Chanel), which appear relatively less frequently than might be expected by virtue of their brand value.

[19] https://www.tyrepress.com/2011/09/michelin-still-top-online-brand-but-the-gaps-narrowing/
[20] https://www.tyrepress.com/2016/10/michelin-returns-to-the-top-of-online-brand-ranking/
[21] https://www.tyrepress.com/2017/09/michelin-tops-online-brand-prominence-table/

Overall, it is not necessarily surprising that there is no strong overall correlation between online prominence and (Kantar) brand value, as they are attempting to quantify distinct brand characteristics. Kantar's report[22] states that their formulation of brand value aims to reflect the financial contribution of the brand to the value of the parent company, and includes direct consideration of consumer perception. Their analysis focuses purely on revenue driven by the brand name under which products and services are sold, as an 'intangible asset', taking into account the following three drivers of value:

- Current demand – the degree to which the brand encourages customers to choose it over competitors
- Price premium – the ability to influence customers to pay more for branded products than for competitors, based purely on the strength of brand equity
- Future demand and price – a reflection of the potential to charge higher prices in the future and to attract new customers

Whilst brand prominence – i.e. online exposure – is part of this picture, there are clearly other factors also at play, and there could certainly be highly valued brands whose business model might mean that they could have little or no significant online presence.

[22] https://www.kantar.com/inspiration/brands/revealed-the-worlds-most-valuable-brands-of-2023: 'Kantar BrandZ brand valuation methodology', pp. 172-174

Conversely, it is also noteworthy that Twitter / X is a key example of a brand which has a significant degree of online presence - potentially due, in part, to its legacy popularity - despite currently not being one of the most valuable brands overall.

Similar comments also apply to the recent analagous study of the top twenty fashion brands, where no strong correlation was observed between prominence and brand ranking (according to the Lyst Index[23]). In this case, part of the difference may be that the Lyst metric is also taking account of other factors, such as brand popularity and customer engagement, in addition to brand value, whereas 'pure' online prominence is a much more specific metric.

Regarding the sentiment measurement in this study, it is notable that that this specific analysis is potentially more likely to identify pages which are, in general, relatively 'neutral' or 'positive' (thereby yielding higher scores), due to the use of generic, business-related search terms which are likely to return official or informational sites. It might be possible to gain more meaningful insights into customer comment through the use of vertical-specific deep dives on subsets of companies, using more focused industry- or product-specific keywords.

Whilst the approach outlined in this article is still relatively rudimentary, it does provide a number of useful insights, and could easily be modified and improved to take account of some of the known shortcomings. Specifically, one obvious area for future development would be the incorporation of additional filtering keywords, to

[23] https://www.lyst.com/data/the-lyst-index/q323/

exclude ‘false positive’ brand mentions (i.e. generic use of the brand name). Beyond this, it would also be informative to attempt to separate out ‘official’ brand uses (e.g. by the brand owner and official partners and representatives) from third-party (‘unauthorised’) use, though this would be likely to require a much more in-depth analysis.

Appendix A:
The top 100 most valuable global brands in 2023

Regex key:

^ Start of string
$ End of string
| Or
? Previous character optional
.? Any optional single character
.* Any number of characters
[^a-zA-Z] Any character other than a letter

Kantar (brand value) ranking	Brand	Brand value ($M)	Category	Brand term	Regex matching string
1	Apple	880,455	Cons. tech. & serv. platf.	apple	[^a-zA-Z]apple|^apple
2	Google	577,683	Media & entertainment	google	google
3	Microsoft	501,856	Bus. tech. & serv. platf.	microsoft	microsoft
4	Amazon	468,737	Retail	amazon	amazon
5	McDonald's	191,109	Fast food	mcdonalds	mcdonald.?s
6	Visa	169,092	Financial services	visa	[^a-zA-Z]visa[^a-zA-Z]|^visa[^a-zA-Z]|[^a-zA-Z]visa$\|^visa$
7	Tencent	141,020	Media & entertainment	tencent	tencent
8	Louis Vuitton	124,822	Luxury	louisvuitton	louis.?vuitton
9	Mastercard	110,631	Financial services	mastercard	mastercard
10	Coca-Cola	106,109	Food & beverages	cocacola	coca.?cola
11	Aramco	105,800	Energy	aramco	aramco
12	Facebook	93,024	Media & entertainment	facebook	facebook

Kantar (brand value) ranking	Brand	Brand value ($M)	Category	Brand term	Regex matching string
13	Oracle	91,992	Bus. tech. & serv. platf.	oracle	oracle
14	Alibaba	91,898	Retail	alibaba	alibaba
15	AT&T	88,999	Telecom providers	att	[^a-zA-Z]at.?t[^a-zA-Z]|^at.?t[^a-zA-Z]|[^a-zA-Z]at.?t$\|^at.?t$
16	Verizon	88,976	Telecom providers	verizon	verizon
17	IBM	87,662	Bus. tech. & serv. platf.	ibm	[^a-zA-Z]ibm[^a-zA-Z]|^ibm[^a-zA-Z]|[^a-zA-Z]ibm$\|^ibm$
18	Moutai	87,524	Alcohol	moutai	moutai
19	Hermès	76,299	Luxury	hermes	hermes|hermès
20	The Home Depot	74,954	Retail	homedepot	home.?depot
21	Nike	74,890	Apparel	nike	[^a-zA-Z]nike[^a-zA-Z]|^nike[^a-zA-Z]|[^a-zA-Z]nike$\|^nike$
22	Accenture	73,640	Bus. tech. & serv. platf.	accenture	accenture
23	UPS	73,598	Logistics	ups	[^a-zA-Z]ups[^a-zA-Z]|^ups[^a-zA-Z]|[^a-zA-Z]ups$\|^ups$

Kantar (brand value) ranking	Brand	Brand value ($M)	Category	Brand term	Regex matching string
24	Nvidia	72,685	Bus. tech. & serv. platf.	nvidia	[^a-zA-Z]nvidia|^nvidia
25	Tesla	67,662	Automotive	tesla	tesla
26	Telekom / T-mobile	65,103	Telecom providers	tmobile	deutsche.?telekom|[^a-zA-Z]t-?mobile|^t-?mobile
27	Starbucks	61,534	Fast food	starbucks	starbucks
28	Walmart	59,873	Retail	walmart	walmart
29	Instagram	58,947	Media & entertainment	instagram	instagram
30	Marlboro	57,576	Tobacco	marlboro	marlboro
31	Chanel	55,939	Luxury	chanel	chanel
32	Qualcomm	54,013	Bus. tech. & serv. platf.	qualcomm	qualcomm
33	Costco	53,383	Retail	costco	costco[^a-zA-Z]|costco$
34	YouTube	53,007	Media & entertainment	youtube	you.?tube
35	Adobe	51,247	Bus. tech. & serv. platf.	adobe	adobe

Kantar (brand value) ranking	Brand	Brand value ($M)	Category	Brand term	Regex matching string
36	Netflix	49,763	Media & entertainment	netflix	netflix
37	LinkedIn	48,529	Media & entertainment	linkedin	linked.?in
38	Cisco	47,171	Bus. tech. & serv. platf.	cisco	cisco
39	Disney	46,970	Media & entertainment	disney	disney
40	Xfinity	44,354	Telecom providers	xfinity	[^a-zA-Z]xfinity|^xfinity
41	TikTok	44,349	Media & entertainment	tiktok	tiktok
42	TCS	41,964	Bus. tech. & serv. platf.	tcs	[^a-zA-Z]tcs[^a-zA-Z]|^tcs[^a-zA-Z]|[^a-zA-Z]tcs$\|^tcs$|tata.?consult
43	Texas Instruments	41,276	Bus. tech. & serv. platf.	texasinstruments	texas.?instruments
44	Intuit	38,617	Bus. tech. & serv. platf.	intuit	[^a-zA-Z]intuit[^a-zA-Z]|^intuit[^a-zA-Z]|[^a-zA-Z]intuit$\|^intuit$
45	L'Oréal Paris	38,084	Personal care	loreal	l.?oreal|l.?oréal
46	Spectrum	37,346	Telecom providers	spectrum	spectrum

Kantar (brand value) ranking	Brand	Brand value ($M)	Category	Brand term	Regex matching string
47	American Express	37,219	Financial services	americanexpress	american.?express|[^a-zA-Z]amex[^a-zA-Z]|^amex[^a-zA-Z]|[^a-zA-Z]amex$\|^amex$
48	SAP	34,874	Bus. tech. & serv. platf.	sap	[^a-zA-Z]sap[^a-zA-Z]|^sap[^a-zA-Z]|[^a-zA-Z]sap$\|^sap$
49	Salesforce	34,709	Bus. tech. & serv. platf.	salesforce	salesforce
50	AMD	33,796	Bus. tech. & serv. platf.	amd	[^a-zA-Z]amd[^a-zA-Z]|^amd[^a-zA-Z]|[^a-zA-Z]amd$\|^amd$|advanced.?micro.?devices
51	RBC	33,744	Financial services	rbc	[^a-zA-Z]rbc[^a-zA-Z]|^rbc[^a-zA-Z]|[^a-zA-Z]rbc$\|^rbc$|royal.?bank.*canada
52	Intel	33,253	Bus. tech. & serv. platf.	intel	[^a-zA-Z]intel[^a-zA-Z]|^intel[^a-zA-Z]|[^a-zA-Z]intel$\|^intel$
53	Wells Fargo	32,466	Financial services	wellsfargo	wells.?fargo
54	Samsung	32,303	Cons. tech. & serv. platf.	samsung	samsung
55	Meituan	32,029	Cons. tech. & serv. platf.	meituan	meituan

Kantar (brand value) ranking	Brand	Brand value ($M)	Category	Brand term	Regex matching string
56	HDFC	31,159	Financial services	hdfc	[^a-zA-Z]hdfc[^a-zA-Z]|^hdfc[^a-zA-Z]|[^a-zA-Z]hdfc$|^hdfc$
57	UnitedHealthcare	30,938	Financial services	unitedhealthcare	united.?healthcare
58	Huawei	30,847	Cons. tech. & serv. platf.	huawei	huawei
59	Haier	30,485	IoT ecosystem	haier	haier
60	Xbox	30,404	Cons. tech. & serv. platf.	xbox	[^a-zA-Z]xbox|^xbox
61	PayPal	30,296	Financial services	paypal	paypal
62	Toyota	28,513	Automotive	toyota	toyota
63	Vodafone	27,030	Telecom providers	vodafone	vodafone
64	JD	26,601	Retail	jdcom	[^a-zA-Z]jd.?com[^a-zA-Z]|^jd.?com[^a-zA-Z]|[^a-zA-Z]jd.?com$|^jd.?com$|jingdong
65	Gucci	26,306	Luxury	gucci	gucci
66	Infosys	26,156	Bus. tech. & serv. platf.	infosys	infosys[^a-zA-Z]|infosys$

Kantar (brand value) ranking	Brand	Brand value ($M)	Category	Brand term	Regex matching string
67	TD	25,969	Financial services	tdbank	[^a-zA-Z]td.?bank[^a-zA-Z]|^td.?bank[^a-zA-Z]|[^a-zA-Z]td.?bank$|^td.?bank$
68	J.P. Morgan	25,429	Financial services	jpmorgan	j.?p.?morgan
69	ICBC	25,419	Financial services	icbc	icbc
70	Shein	24,250	Apparel	shein	shein
71	Mercedes-Benz	23,978	Automotive	mercedes	mercedes
72	Mercado Libre	23,241	Retail	mercadolibre	mercado.?libre
73	China Mobile	23,231	Telecom providers	chinamobile	china.?mobile
74	BCA	22,684	Financial services	bca	[^a-zA-Z]bca[^a-zA-Z]|^bca[^a-zA-Z]|[^a-zA-Z]bca$|^bca$|bank.?central.?asia
75	Chase	22,431	Financial services	chase	[^a-zA-Z]chase[^a-zA-Z]|^chase[^a-zA-Z]|[^a-zA-Z]chase$|^chase$
76	Airtel	22,332	Telecom providers	airtel	[^a-zA-Z]airtel[^a-zA-Z]|^airtel[^a-zA-Z]|[^a-zA-Z]airtel$|^airtel$

Kantar (brand value) ranking	Brand	Brand value ($M)	Category	Brand term	Regex matching string
77	Siemens	22,167	Conglomerate	siemens	siemens
78	CommBank	22,069	Financial services	commbank	commbank|commonwealth.?bank
79	ExxonMobil	22,068	Energy	exxon	exxon
80	KFC	22,056	Fast food	kfc	[^a-zA-Z]kfc[^a-zA-Z]|^kfc[^a-zA-Z]|[^a-zA-Z]kfc$\|^kfc$|kentucky.?fried.?chicken
81	Nongfu Spring	21,764	Food & beverages	nongfuspring	nongfu.?spring
82	Bank of America	21,548	Financial services	bankofamerica	bank.?of.?america
83	Lowe's	21,500	Retail	lowes	lowe.?s[^a-zA-Z]|lowe.?s$
84	NTT	21,385	Telecom providers	ntt	[^a-zA-Z]ntt[^a-zA-Z]|^ntt[^a-zA-Z]|[^a-zA-Z]ntt$\|^ntt$|nippon.?telegraph
85	Ping An	21,183	Financial services	pingan	[^a-zA-Z]ping.?an[^a-zA-Z]|^ping.?an[^a-zA-Z]|[^a-zA-Z]ping.?an$\|^ping.?an$
86	Ikea	21,049	Retail	ikea	[^a-zA-Z]ikea[^a-zA-Z]|^ikea[^a-zA-Z]|[^a-zA-Z]ikea$\|^ikea$

Kantar (brand value) ranking	Brand	Brand value ($M)	Category	Brand term	Regex matching string
87	BMW	20,944	Automotive	bmw	[^a-zA-Z]bmw[^a-zA-Z]|^bmw[^a-zA-Z]|[^a-zA-Z]bmw$|^bmw$
88	Budweiser	19,888	Alcohol	budweiser	budweiser
89	Lancôme	19,400	Personal care	lancome	lancome|lancôme
90	AIA	19,231	Financial services	aia	[^a-zA-Z]aia[^a-zA-Z]|^aia[^a-zA-Z]|[^a-zA-Z]aia$|^aia$
91	Pepsi	18,826	Food & beverages	pepsi	pepsi
92	DHL	18,723	Logistics	dhl	[^a-zA-Z]dhl[^a-zA-Z]|^dhl[^a-zA-Z]|[^a-zA-Z]dhl$|^dhl$
93	Red Bull	18,554	Food & beverages	redbull	red.?bull
94	Zara	18,395	Apparel	zara	[^a-zA-Z]zara[^a-zA-Z]|^zara[^a-zA-Z]|[^a-zA-Z]zara$|^zara$
95	Colgate	18,360	Personal care	colgate	colgate
96	Uber	18,329	Cons. tech. & serv. platf.	uber	[^a-zA-Z]uber[^a-zA-Z]|^uber[^a-zA-Z]|[^a-zA-Z]uber$|^uber$

Kantar (brand value) ranking	Brand	Brand value ($M)	Category	Brand term	Regex matching string
97	FedEx	18,231	Logistics	fedex	[^a-zA-Z]fedex[^a-zA-Z]|^fedex[^a-zA-Z]|[^a-zA-Z]fedex$|^fedex$|federal.?express
98	Shell	17,952	Energy	shell	[^a-zA-Z]shell[^a-zA-Z]|^shell[^a-zA-Z]|[^a-zA-Z]shell$|^shell$
99	Sony	17,814	Cons. tech. & serv. platf.	sony	[^a-zA-Z]sony[^a-zA-Z]|^sony[^a-zA-Z]|[^a-zA-Z]sony$|^sony$
100	Pampers	17,376	Personal care	pampers	pampers

Appendix B:
Formulation of the proximity score for sentiment analysis

The score assigned when a sentiment keyword is identified near to a brand mention is determined by the proximity (in numbers of words) of the two words. In this analysis, we use an exponentially-decaying function (analagous to that used when considering the decay of a radioactive substance according to a half-life).

The proximity score, S_p, is defined as:

$$S_p = \lfloor S_{max} \times (½)^{(p / p_{0.5})} \rfloor$$

where:

S_{max} is the maximum proximity score (i.e. the score for a proximity of 1 word)
p is the proximity (in words)
$p_{0.5}$ is the 'proximity half life' (i.e. the number of words' separation for the proximity score to drop to half of its maximum value)
$\lfloor \rfloor$ denotes the 'floor function' – i.e. rounding the value down to the greatest integer below the value in question

This provides a score profile as shown in Figure B.1.

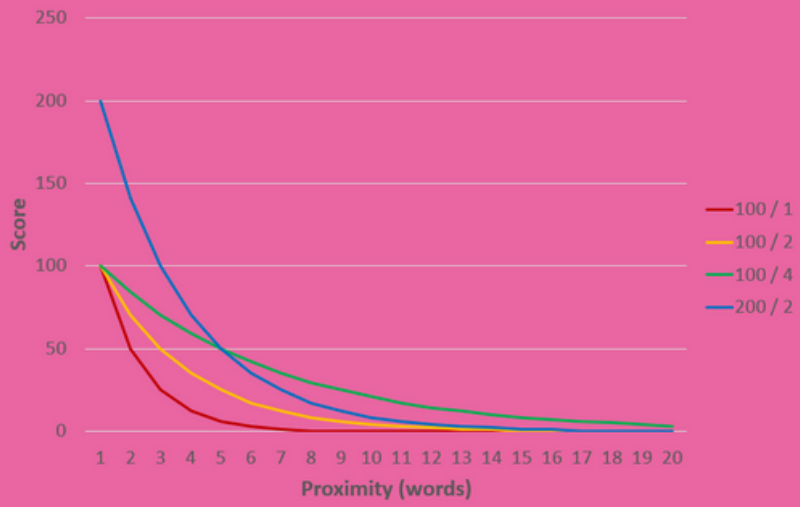


Figure B.1: Proximity scores as a function of proximity, for four combinations of maximum score and proximity half life (shown in the key as: 'maximum score / proximity half-life')

Because of the action of rounding down utilised in the calculation, the maximum score acts as more than just a simple scaling factor; it controls the proximity at which the score drops to zero (i.e. the proximity beyond which a sentiment keyword is deemed not to relate to a brand mention). For the values used in this study (maximum score = 100; proximity half-life = 1 word), the values are as shown in Table B.1.

Proximity (words)	Proximity score
1	100
2	50
3	25
4	12
5	6
6	3
7	1
8	0

Table B.1: Proximity scores for the parameters: maximum score = 100; proximity half-life = 1 word

Appendix C:
Initial tests of the sentiment scoring algorithm

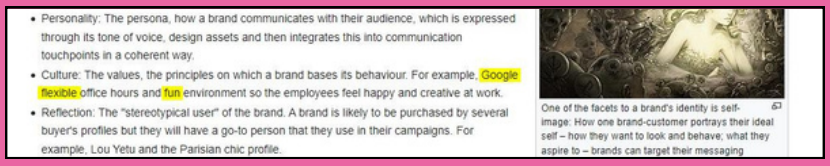
As part of the testing process for the sentiment scoring algorithm, one webpage featuring multiple brand references (https://en.wikipedia.org/wiki/Brand) was analysed to determine the sentiment scores for the top ten most valuable brands, in order to assess the meaningfulness of the results. The results are presented below, as an illustration of the types of content matched by the keyword libraries and proximity score formulation.

Brand term	No. of identified references	Positive sentiment score	Negative sentiment score	Overall sentiment score
apple	4	0	0	0
google	1	106	0	106
microsoft	4	0	0	0
amazon	1	12	0	12
mcdonalds	0	-	-	-
visa	0	-	-	-
tencent	0	-	-	-
louisvuitton	1	3	0	3
mastercard	0	-	-	-
cocacola	12	44	0	44

Table C.1: Numbers of identified references and sentiment scores for each of the top ten brands, on the webpage https://en.wikipedia.org/wiki/Brand

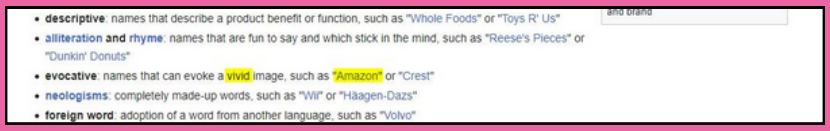
Examples of the brand references contributing to the sentiment scores are shown below.

1. ‘google’ near ‘flexible’ (proximity 1; score component +100) and ‘fun’ (proximity 5; score component +6)

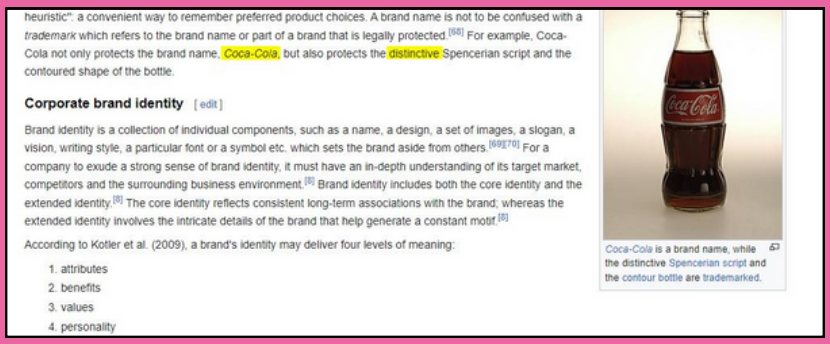

- Personality: The persona, how a brand communicates with their audience, which is expressed through its tone of voice, design assets and then integrates this into communication touchpoints in a coherent way.
- Culture: The values, the principles on which a brand bases its behaviour. For example, Google flexible office hours and fun environment so the employees feel happy and creative at work.
- Reflection: The "stereotypical user" of the brand. A brand is likely to be purchased by several buyer's profiles but they will have a go-to person that they use in their campaigns. For example, Lou Yetu and the Parisian chic profile.

One of the facets to a brand's identity is self-image: How one brand-customer portrays their ideal self – how they want to look and behave; what they aspire to – brands can target their messaging

2. ‘amazon’ near ‘vivid’ (proximity 4; score component +12)


- **descriptive**: names that describe a product benefit or function, such as "Whole Foods" or "Toys R' Us"
- **alliteration** and **rhyme**: names that are fun to say and which stick in the mind, such as "Reese's Pieces" or "Dunkin' Donuts"
- **evocative**: names that can evoke a vivid image, such as "Amazon" or "Crest"
- **neologisms**: completely made-up words, such as "Wii" or "Häagen-Dazs"
- **foreign word**: adoption of a word from another language, such as "Volvo"

3. ‘cocacola’ near ‘distinctive’ (proximity 5; score component +6)


heuristic": a convenient way to remember preferred product choices. A brand name is not to be confused with a *trademark* which refers to the brand name or part of a brand that is legally protected.[68] For example, Coca-Cola not only protects the brand name, Coca-Cola, but also protects the distinctive Spencerian script and the contoured shape of the bottle.

Corporate brand identity [edit]

Brand identity is a collection of individual components, such as a name, a design, a set of images, a slogan, a vision, writing style, a particular font or a symbol etc. which sets the brand aside from others.[69][70] For a company to exude a strong sense of brand identity, it must have an in-depth understanding of its target market, competitors and the surrounding business environment.[8] Brand identity includes both the core identity and the extended identity.[8] The core identity reflects consistent long-term associations with the brand; whereas the extended identity involves the intricate details of the brand that help generate a constant motif.[8]

According to Kotler et al. (2009), a brand's identity may deliver four levels of meaning:

1. attributes
2. benefits
3. values
4. personality

Coca-Cola is a brand name, while the distinctive Spencerian script and the contour bottle are trademarked.

Appendix D:

Overall prominence scores for all 100 brands

Prominence ranking	Kantar (brand value) ranking	Brand term (encompasses all matched variants)	Prominence score
1	2	google	2.856
2	3	microsoft	0.670
3	37	linkedin	0.655
4	4	amazon	0.637
5	12	facebook	0.523
6	34	youtube	0.459
7	29	instagram	0.431
8	1	apple	0.405
9	35	adobe	0.303
10	98	shell	0.168
11	13	oracle	0.157
12	49	salesforce	0.153
13	6	visa	0.143
14	87	bmw	0.129
15	41	tiktok	0.117
16	63	vodafone	0.111
17	48	sap	0.105
18	68	jpmorgan	0.087
19	39	disney	0.078
20	5	mcdonalds	0.073

Prominence ranking	Kantar (brand value) ranking	Brand term	Prominence score
21	36	netflix	0.069
22	52	intel	0.066
23	10	cocacola	0.065
24	86	ikea	0.062
25	84	ntt	0.058
26	99	sony	0.055
27	17	ibm	0.055
28	62	toyota	0.054
29	38	cisco	0.051
30	75	chase	0.051
31	47	americanexpress	0.049
32	21	nike	0.045
33	28	walmart	0.038
34	71	mercedes	0.038
35	60	xbox	0.034
36	25	tesla	0.033
37	22	accenture	0.032
38	54	samsung	0.031
39	9	mastercard	0.031
40	23	ups	0.030
41	53	wellsfargo	0.027
42	83	lowes	0.027
43	91	pepsi	0.027
44	7	tencent	0.026
45	45	loreal	0.024

Prominence ranking	Kantar (brand value) ranking	Brand term	Prominence score
46	95	colgate	0.023
47	77	siemens	0.023
48	65	gucci	0.020
49	79	exxon	0.020
50	46	spectrum	0.019
51	33	costco	0.016
52	44	intuit	0.015
53	27	starbucks	0.015
54	24	nvidia	0.014
55	15	att	0.014
56	11	aramco	0.011
57	61	paypal	0.010
58	74	bca	0.010
59	80	kfc	0.009
60	96	uber	0.009
61	42	tcs	0.008
62	20	homedepot	0.008
63	50	amd	0.007
64	51	rbc	0.007
65	82	bankofamerica	0.007
66	66	infosys	0.006
67	90	aia	0.006
68	14	alibaba	0.005
69	16	verizon	0.005
70	31	chanel	0.005

Prominence ranking	Kantar (brand value) ranking	Brand term	Prominence score
71	56	hdfc	0.005
72	92	dhl	0.005
73	26	tmobile	0.004
74	8	louisvuitton	0.003
75	70	shein	0.003
76	69	icbc	0.002
77	19	hermes	0.001
78	30	marlboro	0.001
79	94	zara	0.001
80	32	qualcomm	0.001
81	58	huawei	0.001
82	64	jdcom	0.001
83	76	airtel	0.001
84	93	redbull	0.001
85	97	fedex	0.001
86	59	haier	0.001
87	100	pampers	0.001
88	43	texasinstruments	0.000
89	67	tdbank	0.000
90	18	moutai	0.000
91	73	chinamobile	0.000
92	78	commbank	0.000
93	85	pingan	0.000
94	88	budweiser	0.000
95	40	xfinity	0.000

Prominence ranking	Kantar (brand value) ranking	Brand term	Prominence score
96	55	meituan	0.000
97	57	unitedhealthcare	0.000
98	72	mercadolibre	0.000
99	81	nongfuspring	0.000
100	89	lancome	0.000

Appendix E:

Additional large Internet and/or social-media brands for analysis

Brand	Regex matching string
Baidu	baidu
Booking.com	booking\.?com
Douyin	douyin
Kuaishou	kuaishou
Pinduoduo	pinduoduo
Pinterest	pinterest
QQ	[^a-zA-Z]qq[^a-zA-Z]|^qq[^a-zA-Z]|[^a-zA-Z]qq$\|^qq$
ServiceNow	service-?now
Sina Weibo	weibo
Snapchat	snap-?chat
Telegram	telegram
Twitter / X	twitter|[^a-zA-Z]x\.com[^a-zA-Z]|^x\.com[^a-zA-Z]|[^a-zA-Z]x\.com$\|^x\.com$
WeChat	wechat
WhatsApp	whats-?app
Yandex	yandex

Regex key:

\. An exact dot (‘.’)

Appendix F:

Overall sentiment scores for all 100 brands*

Sentiment ranking	Kantar (brand value) ranking	Brand term (encompasses all matched variants)	Sentiment score
1	4	amazon	22.48
2	3	microsoft	21.47
3	2	google	20.81
4	12	facebook	13.67
5	1	apple	13.48
6	53	wellsfargo	11.45
7	37	linkedin	10.47
8	49	salesforce	10.45
9	10	cocacola	10.29
10	54	samsung	10.17
11	36	netflix	9.92
12	35	adobe	9.70
13	47	americanexpress	9.70
14	21	nike	9.34
15	34	youtube	9.15
16	60	xbox	8.46
17	23	ups	8.40
18	84	ntt	8.34
19	28	walmart	8.29

* Excluding any brands for which no references were identified

Sentiment ranking	Kantar (brand value) ranking	Brand term	Sentiment score
20	29	instagram	8.20
21	95	colgate	7.74
22	68	jpmorgan	7.11
23	6	visa	6.97
24	9	mastercard	6.65
25	71	mercedes	6.51
26	75	chase	6.43
27	87	bmw	6.32
28	82	bankofamerica	5.97
29	22	accenture	5.62
30	8	louisvuitton	5.37
31	13	oracle	5.17
32	100	pampers	5.00
33	65	gucci	4.59
34	41	tiktok	4.51
35	56	hdfc	4.26
36	89	lancome	4.18
37	33	costco	4.09
38	99	sony	4.01
39	61	paypal	3.42
40	48	sap	3.42
41	26	tmobile	3.10
42	86	ikea	3.09
43	17	ibm	2.98
44	97	fedex	2.95

Sentiment ranking	Kantar (brand value) ranking	Brand term	Sentiment score
45	80	kfc	2.93
46	77	siemens	2.92
47	91	pepsi	2.85
48	38	cisco	2.85
49	7	tencent	2.76
50	98	shell	2.74
51	51	rbc	2.38
52	62	toyota	2.25
53	90	aia	2.22
54	16	verizon	2.07
55	67	tdbank	1.98
56	96	uber	1.75
57	25	tesla	1.64
58	27	starbucks	1.53
59	39	disney	1.39
60	46	spectrum	1.38
61	45	loreal	1.33
62	24	nvidia	1.15
63	66	infosys	1.03
64	92	dhl	1.02
65	52	intel	1.01
66	15	att	1.00
67	31	chanel	0.89
68	44	intuit	0.84
69	32	qualcomm	0.83

Sentiment ranking	Kantar (brand value) ranking	Brand term	Sentiment score
70	19	hermes	0.77
71	5	mcdonalds	0.69
72	50	amd	0.50
73	18	moutai	0.00
74	43	texasinstruments	0.00
75	59	haier	0.00
76	64	jdcom	0.00
77	74	bca	0.00
78	83	lowes	0.00
79	93	redbull	0.00
80	63	vodafone	-0.01
81	94	zara	-0.14
82	42	tcs	-0.30
83	79	exxon	-0.35
84	14	alibaba	-0.53
85	76	airtel	-1.05
86	20	homedepot	-1.36
87	11	aramco	-1.61
88	58	huawei	-1.69
89	70	shein	-2.07
90	69	icbc	-2.71

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