Exploring Patterns of Evolution for Successful Global Brands: A Data-Mining Approach

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Abstract: The sustainable development of a global brand needs to consider the balance between the economy, the environment, and society. Brands that want to be ranked among the best global brands over time need to have competitive strengths, but what defines a successful global brand’s profile is underexplored in the extant literature. This study adopts a data-mining approach to analyze the time-series data collected from Interbrand’s Best Global Brands ranking lists. A total of 168 global brands from 19 countries across 24 industries between 2001 and 2017 were examined. Using the affinity propagation clustering algorithm, this study identified certain patterns of brand evolution for different brand clusters, labeled as fast riser, top tier, stable, slow grower, decline, fall, potential, and so on. Finally, the rankings from 2018 to 2020 were also added to check the model’s predictive power. The findings of this study have important marketing implications.

Keywords: brand value; sustainable brand; data analysis; affinity propagation clustering algorithm

1. Introduction

Since the 1970s, brand-related studies have constituted an important research area in marketing. Brand-building is becoming a “do-or-die” challenge facing large companies nowadays, as the benefits and profits derived from successful brands may constitute their most valuable assets [1,2]. Brand management has gained unprecedented importance in today’s customer-centric societies because winning and keeping customers in the digital marketplace requires an effective development of brand equity [3]. A company with superior brand performance can easily enjoy a highly competitive advantage, especially in the global marketing arena. In general, stronger global brands tend to survive in economic downturns and hardships. Prior studies [4] have also shown that global brands are relatively resilient and can sail against the wind and even grow in turbulent [5] or bear markets. However, due to incessantly changing worldwide environments, even the strongest brands occasionally face unpredictable ups and downs in global markets. To endure market fluctuations, well-designed strategic branding in a global marketing context really matters.

Although brand-building superiority can be manifested in various dimensions such as brand awareness, relevance, differentiation, association, attitude, loyalty, and customers’ advocacy, the overall brand equity is typically considered a “common denominator” of brand performance [2]. Indeed, a closer look at the relevant literature on brand management reveals that many studies address brand equity [6–8], brand value [9], brand valuation [10], and corporate social responsibility (CSR) [11–13]. It now transpires that a critical part of strategic brand management is to build, grow, and sustain brand equity [2]. Against this backdrop of a brand equity-related line of research, the academic inquiries that follow are: (1) Do the paths of growth or decline regarding global brands exhibit certain patterns (if any)? (2) Can different clusters of successful or unsuccessful global brands be detected and identified? (3) It is possible to pinpoint a global brand’s future direction in terms of
upward growth or downward decline? As far as we know, there was scarcely any research addressing these questions, and they are especially worthy of investigation.

To answer the aforementioned questions and see how success stories of standout performers in global branding unfold, we can check and trace brand equity rankings of successful global brands by referring to reports released by leading brand valuation firms. Fortunately, some media or brand consultant companies report the world’s best brand rankings periodically. These brand rankings are believed to affect consumer purchasing preferences, brand loyalty, and stock price [14,15]. In addition, they influence brand owners’ shareholder equity, advertising investment, and evaluation of M&A decisions. In this regard, Interbrand [9,15], a leading brand consultancy for over 40 years, publishes its annual list of best global brands, which is considered to be a reputable measure of the most valuable company brands in the world.

Thus far, the extant studies that use the best global brands rankings published annually by Interbrand are relatively limited [9,11,13,15,16]. This study narrows the research gap and aims to explore and identify possible patterns of brand value development for best global brands reported annually by Interbrand. Specifically, we want to answer the following research questions: What are the profiles of the best global brands in the ranking list? What are the trajectories (in terms of brand value) exhibited by these best global brands over time? Is it possible to forecast the listed brands’ future positions using historical data? Essentially, using the best global brand ranking data provided by Interbrand, this paper adopts a data-mining approach to uncover the hidden pattern or characteristics of these brands and examine their changes over time.

The reasons by which global brand stature is related to sustainability are as follows. In light of the 17 Sustainable Development Goals (SDGs) [17] promoted by the U.N. Assembly in 2015, companies are incessantly enhancing their commitment to CSR to obtain legitimacy and reputation, and to create shared value for stakeholders and foster relationships with them [18]. If global companies can position their brands as highly responsible, sustainable, and ethical by enforcing active CSR strategies, they can naturally gain strength [19]. In the wake of corporate concerns for sustainable development, the integration of sustainability into core business strategies has permeated in various levels of corporate decisions [20]. Environmental commitments made by top-ranking firms have gradually become the key-stone of their brand uniqueness. As highlighted in Interbrand’s Best Global Brands 2020 report, “climate change is the next apocalyptic event we face, so sustainability has to become a radical priority for organizations and brands” (p. 3). The 2020 rankings show that Microsoft, the bronze award winner, has set a goal of becoming carbon negative (not just neutral) before 2030, while Shell disappeared from the Best Global Brands list. For top-notch brands to maintain their incumbent status, pursuing SDGs through CSR activities may offer other advantages such as exploring new businesses opportunities, formulating different business models, and stimulating innovation strategies, which usually result in improved business performance and shining brand ranking.

The empirical parts of this paper are divided into three studies. Study 1 tries to depict the profiles of the best global brands based on Interbrand’s rankings between 2001 and 2017. We analyze 168 brands from 19 countries of origin across 24 industries in the 2001–2017 period. Study 2 uses the affinity propagation clustering (AP clustering) algorithm [21] to explore the evolution of the best global brands over time. We investigate the longitudinal patterns of best global brands in terms of their rankings, such as top winner, fast riser, and slow grower, as well as their decline, fall, and future potential. In Study 3, additional brand ranking data between 2018 and 2020 are affixed to the clustering results, and the possible evolutionary paths of these brands are projected and discussed.

2. Literature Review

2.1. Global Branding

Global branding [22,23] represents a strategy by which products in a strategic planning process, at least to some extent, attain the goal of cost reduction and achievement
orientation from the manifold benefits of a brand awareness that permeates the world market [22]. Studies related to global brands have focused on global-local branding practices, cross-cultural issues, and consumer reactions [24]. Furthermore, Chabowski et al. [23] highlighted the major research topics in global branding, including international branding strategy, brand positioning, branding and country of origin, brand image, and brand performance. Strong brands [25] can be sources of firms’ competitive advantage and positively affect corporate revenue and shareholder equity [26,27]; however, global brands may be adversely affected during a turbulent time [16,26,28,29]. Furthermore, it should be noted that brand equity and brand value change in response to a firm’s sustainable management strategy [12,30–36].

Global brands may be affected in times of uncertainty [37]. Dorfleitner et al. [4] pointed out that during an economic depression, the financial performance of global brands is better than that of generic brands. Their study also indicated that business services, technology, and retail are vital industries that drive performance. Suder et al. [5] used longitudinal brand ranking and cross-sector and cross-industry data to explore the performance of global brand management in the five consecutive years after the 9/11 terrorist attacks. Johansson et al. [16] investigated the financial performance of some resilient brands in the US market during the 2008 financial crisis. Extending two previous studies, Suder and Suder [29] examined the evolution of global brands over the decade following 9/11. They focused on the effect of macroeconomic threats, including the financial crisis, terrorism, and warfare. They found that geopolitical events significantly impacted brand value compared to those events related to the financial crisis. In 2020, the COVID-19 pandemic has caused tremendous threats to global public health and brought about widespread political, economic, and financial collapse [37]. Given the negative effects of environmental uncertainty on business operations, further analyses of the evolution and sustainability of global brands should be expected [32,35,36]. Since different global brands may exhibit different growth trajectories and distinct transformation processes, examining the pattern of changes over time via data science is worthwhile.

2.2. Best Global Brands Ranking

Currently, several marketing studies and consulting companies have developed different frameworks and tools for the valuation of brands, of which primarily consulting companies have developed different frameworks and tools for the valuation of brands, primarily combining corporate financial figures from the capital market, expert evaluations, and consumer research findings [25,38–41]. Examples of some well-known brand rankings include Interbrand’s Best Global Brands [15], BrandZ’s Top 100 Most Valuable Global Brands [42], Forbes’ The World’s Most Valuable Brands [43], and Brand Finance Global 500 [44]. These brand ranking reports have emerged as important references and research tools for marketing decision-makers and researchers.

The merits of any brand’s inclusion in a ranking list are multifold. The listing of a company brand can directly boost the corresponding firm’s stock price, increase corporate profits and shareholder value, encourage corporate investment, and expand future marketing budgets. Moreover, it can raise brand equity and corporate assets, thereby improving asset valuation in mergers and acquisitions.

Some studies have mentioned the effects of brands being listed in the best global brands ranking. Dorfleitner et al. [4] compared the financial performance of brands listed by Interbrand, Forbes, and BrandZ and found that brand performances would not be caused by differences in brand ranking methods. Dutordoïr et al. [14] found that the release of brand value had a significant impact on stock returns. Madden et al. [27] established that company brands listed as top performers achieved higher returns and reduced risks. Ratnatunga and Ewing [45] extended the brand valuation model by developing the brand capability value approach, which estimated the future impact of marketing budgets and branding decisions on brand value.
Among the brand ranking consultancy firms, Interbrand has formed a network of 29 offices in 22 countries to achieve global and regional diversity and has published rankings of regionally successful brands for different countries or industrial sectors. Interbrand has been considered the pioneer in ranking the world’s best global brands since 2000. Moreover, Interbrand’s renowned brand valuation methodology contains three components: (1) financial performance of branded products or services, (2) the roles played by the brand in buyer purchase decisions, and (3) the brand’s competitive strengths. Thus, Interbrand’s Best Global Brands ranking list was chosen as the source of brand ranking data in this study.

2.3. Data Analysis

This study adopted a data-mining approach [46] to discover the underlying growth patterns of brands included in Interbrand’s best global brands ranking list. It is a longitudinal study using historical data provided by Interbrand. Extensive data mining has been used in academia as well as in practice [47–49]. Sivarajah et al. [49] studied Scopus database from 1996 to 2015 and concluded that data science could be applied to different fields of management in various ways, for example, by exploring the digital text [50,51] or visual materials [52] related to consumptions. Findings obtained from the application of data science are more objective than expert opinions, and it is more plausible to identify patterns and trends from a longitudinal viewpoint. For example, Berndt [53] introduced the dynamic time warping (DTW) technique to find patterns in time series data.

Most data-mining methods are based on techniques from machine learning, pattern recognition, and other statistics methods. Clustering analysis is one typical application in data mining; it can approximate the internal structural and spatial characteristics of massive data samples. Clustering analysis is used in situations such as virus research data, face and fingerprint recognition, and financial stock market prediction. Frey and Dueck [21] used AP clustering to solve the problem of choosing an initial class representative point in the early stages of clustering. AP clustering can be applied to identify genes in microarray data, representative sentences in manuscripts, and cities that are efficiently accessed by airline travel.

Compared with the classical K-Means clustering algorithm, AP clustering does not require the specification of K (classic K-Means) or other parameters that describe the number of clusters. AP exhibits a clear center of mass (cluster center). All the data points in the sample may become the center in the AP algorithm, known as the exemplar, compared with the cluster center (such as K-Means) being obtained by averaging multiple data points. Since specifying the clustering center in advance is not required in the application of the AP clustering algorithm, Li et al. [54] developed a dynamic-model-based time series data mining approach to analyze the correlations of sales among different commodities. In this study, AP clustering was applied to explore patterns of the evolution of global brands using Interbrand’s time series data.

3. Materials and Methods

3.1. Data Source

Interbrand has used brand equity as a ranking criterion, making it the company to do so for the longest time. Its annual “Best Global Brands” reports includes financial analysis, the role of brands, and brand strengths (see in Supplementary Materials). Reports provided by Interbrand become a shared data source for brand rankings often used in academic research. Interbrand listed 75 brands in its valuable brands rankings in 2000, and has been highlighting the 100 best brands of the world since 2001. Along with expert evaluations and financial reports, the format of the Best Global Brands ranking reports has not changed significantly over the years. For this study, time series data were collected based on Best Global Brands ranking lists from 2001 to 2017. The dataset contains basic characteristics, countries of origin, and industrial sectors of listed brands.
3.2. Affinity Propagation Clustering Algorithm

To explore the evolution of global brand ranking, the AP clustering algorithm [21] that conducts a similarity matrix analysis of the clustering method was employed. This algorithm can identify exemplars among data points as well as form clusters of data points around the exemplars. AP operates by simultaneously considering all data points as potential exemplars and exchanging messages between the data points until the emergence of a suitable set of exemplars and clusters. It takes the measures of similarity between the pairs of data points as inputs.

In AP clustering algorithms, all the samples are considered data points (or an $n \times m$ similarity matrix $S$ for $n$ data points) of the group; consequently, the cluster centers (or exemplars) of all the data points are computed through the transmission of messages to each data point in the cluster. In the clustering process, two types of messages are transmitted among the data points: responsibility and availability. Responsibility denotes the messages sent from cluster members to candidate exemplars (similar to the center of a cluster); it indicates the suitability of a data point as a member of the candidate exemplar’s group. In contrast, availability conducts the transmission of messages from candidate exemplars to potential cluster members, exhibiting the appropriateness of the candidate as an exemplar.

AP is regarded as a type of time series data mining [21,55,56], which helps in the discovery of valuable information and exciting patterns related to time series datasets. Furthermore, it includes a time series for clustering and classification, which applies to various fields of study. To the best of our knowledge, no prior research has employed AP clustering to determine the association and correlation among different brands using time series data mining [55,56]. In this study, the AP clustering technique was utilized to explore the transformation of brands and determine the different transformation patterns of global brands. We proposed a combined model with time series data mining for the correlation analysis of international brands via distance models that measure the similarity between any two sequences and models that transform from the original time series.

A similarity measure performs the basic work in time series data mining [57]. It is often transformed with the distance measures that are used to compute the degree of correlation between two time series. In this study, DTW [54,58] was used instead of the Euclidean distance. DTW is the accumulated sum of the warping distance between every pair of time points with different values on the time axes; hence, it is also the best warping path. DTW could be written as $D(A,B) = \text{DTW}(A,B)$. It can measure the similarity between two time series with unequal lengths.

After setting a similarity matrix that emerges from the collection of real valued similarities between every time series pair, the AP clustering is completed and two kinds of messages, responsibility and availability, are updated to select the exemplar points of the clusters. As shown in Figure 1, data points need to cluster, such that AP clustering can automatically divide them into four groups after executing 20 iterations. The exemplar points in red represent the center points of the corresponding clusters. It possesses a representative ability in the related groups to a certain extent. Suppose that several time series are required to be clustered; they are denoted as $S = \{S_1, S_2, \ldots, S_N\}$, where $S_1$ is the first time series in the dataset $S$, and $N$ denotes the total number of time series considered.
Figure 1. The affinity propagation clustering algorithm process.

3.3. Process

In Study 1, the profiles of the best global brands were analyzed by the dataset on their ranking as shown in Table 1. Data were collected from the ranking lists of Interbrand’s Best Global Brands from 2001 to 2017. There were 100 brands in each annual ranking list for over 17 years. The brand name, origin, sector, and order of ranking were considered for the analysis.

Table 1. The origins of Interbrand’s Best Global Brands (2001 to 2017).

| Origin  | Brand | Origin  | Brand | Origin  | Brand | Origin  | Brand |
|---------|-------|---------|-------|---------|-------|---------|-------|
| US      | 92    | Switzerland | 8     | Denmark | 2     | Finland | 1     |
| France  | 11    | Italy    | 5     | Spain   | 2     | Ireland | 1     |
| Germany | 11    | Netherlands | 4     | Canada  | 2     | Mexico  | 1     |
| UK      | 9     | South Korea | 4     | China   | 2     | Taiwan  | 1     |
| Japan   | 9     | Sweden   | 4     | Bermuda | 1     | Total   | 168   |

To capture the dramatic changes experienced by global brands in the longitudinal study, the AP clustering algorithm was adopted to determine the similarity between objects. The process for Study 2 was as follows:

1. Set the brand’s value based on its ranking; that is,

$$S'_i(j) = \begin{cases} 
101 - S_i(j) & S_i(j) \leq 100 \\
0 & S_i(j) > 100 
\end{cases}$$

i.e., rank 1 = 100, rank 100 = 1; a rank below the top 100 = 0.

2. Compute the distance $D(i,j)$ based on DTW for each pair of brand time series, and create a distance matrix $D$, $D(i,j) = DTW(S'_i, S'_j)$.

3. Transform the distance matrix to the similarity matrix used in AP clustering; that is, $S = D \times (-1)$

4. Preference is the median of the similarity matrix; that is, $P = \text{median}(S)$.

5. Use $idx$ to record the index of the representative exemplar for every time series after executing the AP clustering method, that is, $idx = AP(S, P)$, where $idx(i)$ records the index of the $i$th brand’s representative exemplar.

6. Objects with the same representative exemplar are in the same group and a cluster. $\text{Lab} = \text{unique}(idx)$ is a vector recording the indices of the different representative exemplars. Let $C_k$ be null initially, such that $C_k = C_k \cup i$ if $idx(i)$ is equal to $\text{Lab}(k)$. 
Further analysis on performance is based on the visualization and hierarchical clustering result for each brand group in the AP clustering results.

AP clustering was used to develop another method, where we standardized the brands’ time series ranking information to identify their ranking transformation based on the shape of change trend. After examining the significance of two different results from the two-category cluster analysis based on ranking value and the evolution trend of standardization, we only reserved the former to show clustering by brand ranking value.

In Study 3, a new ranking database was added for the 2017–2020 period to serve as a validation group for prior research. The change observed in these four years was applied to the results of Study 2 to test the predictability.

4. Results

4.1. Study 1 Results: Profile of the Best Global Brands

The results show that 168 different global brands appeared on the top 100 list from 2001 to 2017. The average time during which these brands remained in the top 100 was over 10 years, while 65% of them held the position for more than 15 years. Only 10% changes were observed in Interbrand’s ranking list year by year. Table 1 shows that the best global brands are from 19 different regions. Most of the brands originated from the United States (92), followed by France (11), Germany (11), the United Kingdom (9), Japan (9), Switzerland (8), Italy (5), the Netherlands (4), South Korea (4), Sweden (4), Denmark (2), Spain (2), Canada (2), China (2), and others (5). The outperforming global brands are mostly from the US, other countries in the Group of 7 (G7), and other developed countries.

Table 2 presents the best global brands from 24 different industries. These include fast-moving consumer goods (FMCG) (21), financial services (19), automotive (19), technology (15), alcohol (12), electronics (12), luxury (12), media (8), business services (7), apparel (6), diversified (6), restaurants (5), beverages (4), internet services (6), energy (3), pharmaceuticals (3), sporting goods (3), transportation (4), hospitality (2), home furnishings (1), tobacco (1), telecommunication (1), toys and games (1), and enterprises (1). Most well-known global brands come from the FMCG, financial services, automotive, technology, alcohol, electronics, and luxury sectors. Technological brands seem to have a faster pace of growth than others.

Table 2. Breakdown of the 168 brands (2001–2017) by industry sectors.

| Sector            | N  | Sector    | N  | Sector    | N  | Sector    | N  |
|-------------------|----|-----------|----|-----------|----|-----------|----|
| FMCG              | 21 | Luxury    | 12 | Beverages | 4  | Hospitality| 2  |
| Automotive        | 18 | Media     | 8  | Internet Services | 4 | Home Furnishings | 1 |
| Financial Service | 20 | Business Service | 7 | Energy   | 3  | Tobacco    | 1  |
| Technology        | 15 | Apparel   | 6  | Pharmaceuticals | 3 | Telecommunications | 1 |
| Alcohol           | 12 | Diversified | 6 | Sporting Goods | 3 | Toys & Games | 1 |
| Electronics       | 12 | Restaurants| 5 | Transportation | 3 | Enterprise  | 1 |

4.2. Study 2 Results: Trends of Evolution Based on the Value of the Ranking Lists

The Gephi software was used to show the clustering results via visualization tools. The grouping results are first shown in Figure 2, where each brand connects to the exemplar brand in a group. Distances between two brands can be denoted by curved lines, and these curved lines emoted from an exemplar and were connected with its corresponding brands. In Figure 3, the details of each group’s trend and hierarchical clustering were summarized. There are 11 exemplars (groups), such that the exemplar brands and the number of brands belonging to each group (dubbed as “account number”) are as follows: V1—Facebook (9), V2—Gillette (27), V3—GUCCI (10), V4—Adobe (19), V5—Hewlett Packard (9), V6—Caterpillar (9), V7—Compaq (7), V8—AIG (4), V9—Boeing (26), V10—Ericsson (8), and V11—Dior (40).
Figure 2. V. group—Visualization of the 11 brands’ clustering results based on the value of the ranking list.
Trends

V1 Fast Riser
Facebook:9

V2 Top tier
Gillette:27

V3 Stable
GUCCI:10

V4 Slow grower
Adobe:19

V5 Sudden entrant
Hewlett Packard:9

V6 Unstable
CATERPILLAR:9

Hierarchical clustering

Figure 3. Cont.
Figure 3. The V. groups’ trend and hierarchical clustering results from Study 2.
As shown in Figure 3, the brands’ evolution trends clustered by their ranking value for each group can be observed. They share the same evolution trend due to similarity between each brand and its exemplar in a group. Each group was given a name according to their evolution trends, such as V1—Fast riser, V2—Top tier, V3—Stable, V4—Slow grower, V5—Sudden entrant, V6—Unstable, V7—Fall, V8—Short lived, V9—Decline, V10—Drop, and V11—Potential, as shown in Table 3. From Figure 3, we can also observe the level of similarity for each pair of brands: a short distance between two brands implies that their trends are highly similar.

**Table 3.** The exemplar groups, account number, and trend description of Study 2 results.

| Value | Exemplar     | N  | Description       |
|-------|--------------|----|-------------------|
| V1    | Facebook     | 9  | Fast Riser        |
| V2    | Gillette     | 27 | Top Tier          |
| V3    | GUCCI        | 10 | Stable            |
| V4    | Adobe        | 19 | Slow Grower       |
| V5    | Hewlett Packard | 9 | Sudden Entrant    |
| V6    | Caterpillar  | 27 | Unstable          |
| V7    | Compaq       | 10 | Fall              |
| V8    | AIG          | 4  | Short lived       |
| V9    | Boeing       | 26 | Decline           |
| V10   | Ericsson     | 8  | Drop              |
| V11   | Dior         | 40 | Potential         |

4.3. Study 3 Results: Mapping the Evolution Trend of Interbrand’s Rankings from 2018 to 2020

In Study 3, Interbrand’s Best Global Brands rankings from 2018 to 2020 were affixed to the original dataset, and projections of some brands’ evolution paths are discussed. A total of 175 brands were found to be in the top 100 list between 2001 and 2020. Table 4 shows the difference in terms of brands’ country of origin between 2001–2017 and 2001–2020 periods.

**Table 4.** The origins of Interbrand’s Best Global Brands (2001–2017 and 2001–2020).

| Origin     | 2001–2017 | %   | 2001–2020 | %   |
|------------|-----------|-----|-----------|-----|
| US         | 91        | 54% | 97        | 55.4% |
| France     | 11        | 6.6%| 11        | 6.3% |
| Germany    | 11        | 6.6%| 11        | 6.3% |
| UK         | 9         | 5.5%| 9         | 5.1% |
| Japan      | 8         | 4.8%| 9         | 5.1% |
| Switzerland| 8         | 4.8%| 8         | 4.7% |
| Italy      | 5         | 3%  | 5         | 2.9% |
| Netherlands| 4         | 2.3%| 4         | 2.3% |
| South Korea| 4         | 2.3%| 4         | 2.3% |
| Sweden     | 4         | 2.3%| 4         | 2.3% |
| Denmark    | 2         | 1.1%| 2         | 1.1% |
| Spain      | 2         | 1.1%| 2         | 1.1% |
| Canada     | 2         | 1.1%| 2         | 1.1% |
| China      | 2         | 1.1%| 2         | 1.1% |
| Others     | 5         | 3%  | 5         | 2.9% |
| Total      | 168       | 100 | 175       | 100%|

Table 5 and Figure 4 show the industrial composition of Interbrand’s Best Global Brands from 2017 to 2020. The automotive, financial service, technology, luxury, and FMCG sectors were identified as the major international brand sectors. Business service, media, and internet services, such as technology, were observed to be the growing sectors.
Table 5. Breakdown of the top 100 brands (2017–2020) by industry sectors.

| Sector          | 2017 | 2018 | 2019 | 2020 |
|-----------------|------|------|------|------|
| Alcohol         | 7    | 6    | 6    | 6    |
| Apparel         | 2    | 2    | 2    | 2    |
| Automotive      | 15   | 16   | 15   | 15   |
| Beverages       | 4    | 4    | 3    | 3    |
| Business Service| 6    | 5    | 5    | 7    |
| Diversified     | 5    | 5    | 5    | 5    |
| Electronics     | 4    | 5    | 5    | 6    |
| Energy          | 1    | 1    | 1    | 0    |
| Enterprise      | 1    | 1    | 1    | 0    |
| Financial Service| 12  | 12   | 12   | 12   |
| FMCG            | 9    | 9    | 9    | 9    |
| Logistics       | 0    | 0    | 0    | 3    |
| Home            | 1    | 1    | 1    | 0    |
| Furnishings     | 0    | 0    | 0    | 0    |
| Hospitality     | 0    | 0    | 0    | 0    |
| Internet Services| 3   | 4    | 3    | 0    |
| Luxury          | 8    | 9    | 9    | 9    |
| Media           | 3    | 3    | 6    | 7    |
| Pharmaceuticals | 0    | 0    | 0    | 0    |
| Restaurants     | 3    | 3    | 3    | 3    |
| Retail          | 0    | 0    | 0    | 2    |
| Sporting Goods  | 2    | 2    | 2    | 2    |
| Technology      | 11   | 9    | 9    | 9    |
| Telecommunications| 0  | 0    | 0    | 0    |
| Tobacco         | 0    | 0    | 0    | 0    |
| Toys & Games    | 0    | 0    | 0    | 0    |
| Transportation  | 3    | 3    | 3    | 0    |
| 100             | 100  | 100  | 100  | 100  |

FMCG = fast moving consumer goods.

Figure 4. Breakdown of the top 100 brands (2017–2020) by industry sectors in histograms.
After affixing the additional 2018–2020 brand rankings to the 2001–2017 original dataset, the possible inclusion of certain brands in a specific exemplar group can be predicted. In Part A of Table 6, the 2018–2020 updated rankings of some major brands that were mostly listed among the top 100 during 2001–2017 are provided. Notice that NETFLIX and TESLA are identified as belonging to the V11—potential group, along with Salesforce, John Deere, Corona, Dior, and Johnnie Walker. Furthermore, we can observe brands following a “fading trend,” including Harley Davidson (V10—Drop), Discovery, Sprite, Shell, and PRADA (V6—Unstable). The future prospect of SMIRNOFF and Moët & Chandon (V9—Decline) is even worse. On the contrary, Part B of Table 6 gives examples of brands that disappeared in 2017 but somehow managed to come back in later years. Some brands that were dropped off the top 100 brand list in 2017 quickly reappeared between 2018 and 2020, namely, Chanel, Spotify, Nintendo, and Hennessy. Yet the patterns of their resurging are somewhat difficult to predict. Overall, the AP clustering method in Study 2 still seems to have some explanatory power when applied to a larger dataset.

Table 6. Expected changes of major brands’ Interbrand rankings from 2017 to 2020.

| Part A | Brand     | 2017 | 2018 | 2019 | 2020 | Sector         | Origin          | Value | Trend  |
|--------|-----------|------|------|------|------|----------------|-----------------|-------|--------|
| Oracle | 17        | 20   | 18   | —    | —    | Business Services | USA            | V2    | Top Tier |
| Adobe  | 56        | 51   | 39   | 27   | —    | Technology      | USA            | V4    | Slow Grower |
| Thomson Reuters | 66 | —    | —    | —    | —    | Business Services | Canada         | V3    | Stable   |
| Harley Davidson | 77 | 93   | 99   | —    | —    | Automotive      | USA            | V11   | Potential |
| NETFLIX | 78      | 66   | 65   | 41   | —    | Media          | USA            | V10   | Drop     |
| Discovery | 79      | 81   | 91   | —    | —    | Media          | USA            | V11   | Potential |
| Salesforce | 84      | 75   | 70   | 58   | —    | Business        | USA            | V11   | Potential |
| Sprite  | 90        | 96   | —    | —    | —    | Beverages       | USA            | V6    | Unstable |
| Shell   | 91        | 89   | 97   | —    | —    | Energy         | Netherlands     | V6    | Unstable |
| John Deere | 92      | 88   | 84   | 89   | —    | Diversified    | USA            | V11   | Potential |
| Corona  | 93        | 85   | 79   | 78   | —    | Alcohol        | Mexico          | V11   | Potential |
| PRADA   | 94        | 95   | 100  | 99   | —    | Luxury         | USA            | V6    | Unstable |
| Dior    | 95        | 91   | 82   | 83   | —    | Luxury         | France          | V11   | Potential |
| Johnnie Walker | 96 | 97   | —    | 98   | —    | Alcohol        | UK             | V11   | Potential |
| SMIRNOFF | 97      | —    | —    | —    | —    | Alcohol        | UK             | V9    | Decline  |
| TESLA   | 98        | —    | —    | 40   | —    | Technology     | USA            | V11   | Potential |
| Moët & Chandon | 99 | —    | —    | —    | —    | Alcohol        | France          | V9    | Decline  |

| Part B | Brand    | 2017 | 2018 | 2019 | 2020 | Sector     | Origin  | Value | Trend |
|--------|----------|------|------|------|------|------------|---------|-------|-------|
| Instagram | —       | —    | —    | —    | 20   | Media      | USA     | V9    | Decline |
| CHANEL   | —       | 23   | 22   | 21   | —    | Luxury     | France  | V9    | Decline |
| YouTube  | —       | —    | —    | 30   | —    | Media      | USA     | V10   | Drop   |
| Spotify  | —       | 92   | 92   | 70   | —    | Media      | Sweden  | —     | —     |
| Nintendo | —       | 99   | 89   | 76   | —    | Electronics | Japan   | V10   | Drop   |
| LinkedIn | —       | —    | 98   | 90   | —    | Media      | USA     | V11   | Potential |
| Hennessy | —       | 98   | 95   | 91   | —    | Alcohol    | France  | —     | —     |
| Uber     | —       | —    | 87   | 96   | —    | Technology | USA     | —     | —     |
| Zoom     | —       | —    | —    | 100  | —    | Technology | USA     | —     | —     |

5. Discussion

5.1. Academic Contribution

This study attempted to fill the research gaps and make the following contributions.

(1) For top-ranking global brands and the companies running them, it is natural to assume that they can beat their competitors with better and smarter branding strategies [7]. So, the ranking of brand performance may contain certain secrets of their success. This study conducted a preliminary investigation into Interbrand’s 20-year ranking data [15], to delineate the hidden profile of successful global brands. By analyzing successful global
brands’ history of sustaining their competitive edge, we can gain a better picture of their brand prominence and perceive future marketing implications.

A descriptive investigation of our data shows that the best international brands originated from 19 countries, and most brands originated from developed countries, with US brands’ supreme dominance in the ranking list, followed by other G7 countries. Only a few brands originated from emerging economies (such as Asia). These global brands mainly comprised 24 distinct industry sectors, with automotive, business services, luxury, and FMCG as the major sectors. Technology and media industries have been growing from the scene.

(2) It is probably the first empirical study to adopt the AP clustering method [21] in the analysis of global brand rankings time-series data. Two different clustering methods were used: a two-category cluster analysis based on ranking value, and the evolution trend of standardization. The resulting 11 exemplar brand groups demonstrate somewhat different patterns in shape, which can be labeled as fast riser, top tier, slow grower, stable, unstable, decliner, fall, short-lived, potential, and so on. The classification of exemplar groups or clusters has profound marketing implications.

(3) The AP clustering method has the potential of predicting a brand’s future ranking; however, its predictive power is yet to be verified in future studies. Thus far, this method is quite useful in classifying different brand groups. It could be regarded as the basis for preliminary research such as ours.

5.2. Practical Contribution

This study provides an overview of what most successful global brands look like in terms of brand performance rankings. From 2001 to 2020, 40, 72, and 99 brands have retained their ranking positions in the list for the past 20 years, for more than 15 years, and for more than 10 years, respectively. This information shows the importance of sustainable brand management in the marketplace. On average, only a 10% change was observed in the ranking list every year, meaning that 90% of the best global brands are defending winners. From the dataset, we found that the most significant periods of ranking change were 2008 to 2010, 2003 to 2005, 2001 to 2002, and 2017 to 2018, which coincided with financial crises and economic depressions [28,29,37]. The profound changes between 2019 and 2020 are unprecedented. Future studies could help identify positive factors that promote brand growth even in unfavorable times or the reasons for the rapid degeneration of certain brands. For sustainable brand management, firms must match their well-designed branding strategies [5,8,11,28] with constantly changing environments.

The reasons by which most successful global brands originated in countries such as the US, France, and Germany deserve further attention. There may be historical, cultural, social, political, or psychological explanations to this observation. Still, we believe that the most crucial issue should be how US, French and German companies build and manage strong brands with competitive strategies over time [13]. Quite a few crucial lessons can be learned here. Nevertheless, brand image may be subject to changes due to country stereotyping, animosity or political confrontations among countries, antagonism, protectionism, social movements, ideological divergence, religious conflicts, and so on. Recently, environmental concerns have become an emerging issue in global branding [59]. To achieve the UN’s SDGs, global brands must adhere to certain sustainability standards. Thus, it is necessary to explore global issues with widespread influences to maintain a brand’s stature in the marketplace [60].

Finally, global industries are bound to face business cycle fluctuations and paradigm shifts. Owing to technological advancements following the advent of the Internet age, many brands have crossed the traditional industry boundaries through diversifications, brand extensions, and co-marketing or alliance strategies. The boundaries between different industries have increasingly become blurred. Recently, ICT firms and information services providers have been making impressive progress, and companies such as Google and
Amazon have become global business leaders. Meanwhile, the long-term sustainable development of apparel, automobiles, commerce, financial services, FMCG, luxury goods, and media industries deserves to be further examined.

5.3. Limitation and Future Research

This study had some limitations due to its research design. First, we chose Interbrand’s best global brand lists because Interbrand is considered to be an authentic provider of brand performance rankings. However, to increase the validity of this research, future analyses should include other brand ranking databases. Second, a data-mining approach was applied to examine the growth patterns of successful global brands, and the AP clustering method was used. Future studies involving analyses of brand evolution patterns or trends may resort to other methodologies to generate more rigorous research findings. Finally, it would be insightful to understand why different firms in the same industry unveil different brand evolution paths. For example, many technological brands belong to the top tier or fast riser groups; however, Yahoo falls in the decliner group. To find out possible firm heterogeneity, we may use text-mining methods and search for textual clues contained in annual brand ranking reports to understand why some brands are successful while others fail.

Supplementary Materials: The ranking data resource of Interbrand Best Global Brands are available online at https://interbrand.com/best-brands (accessed on 1 June 2021).

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