Career Trajectory and Success of Neurosurgeons

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Part 1: Introduction

1.1 Personal Engagement

I have always been fascinated by the potential influence of personal characteristics on professional success. In particular, the impact of name characteristics and facial memorability scores on the career trajectory of individuals has captured my attention. The idea that something as seemingly trivial as a person's name or the memorability of their face could play a role in their professional outcomes is both intriguing and thought-provoking.

1.2 Research Question

Building upon this curiosity, the central research question of this paper emerges: What is the impact of name characteristics and facial memorability score on the career trajectory and success of neurosurgeons, as measured by bibliometric data? The potential relationship between name attributes, facial memorability, and the professional outcomes of neurosurgeons will be uncovered by exploring this question.

1.3 Hypothesis

In this paper, the following hypotheses are proposed regarding the influence of name characteristics and facial memorability score on the career trajectory and success of neurosurgeons:

- Null Hypothesis (H0): There is no significant impact on neurosurgeons' career trajectory and success when varying name characteristics and facial memorability scores.
- Alternative Hypothesis (HA): There is a significant impact on neurosurgeons' career trajectory and success when varying name characteristics and facial memorability scores.

Part 2: Background

2.1 Methodology Background

The research methodology primarily relies on a combination of human-based and website-based data collection approaches. The process consists of three key components: gathering bibliometric data from the Scopus website, obtaining data related to the characteristics of neurosurgeons' names primarily from the Forebears and Namsor website, and acquiring memorability scores for neurosurgeons' faces using Resmem.

2.2 Variables Background

2.2.1 Independent Variables

a) Name Characteristics

The alternative hypothesis suggests that name characteristics may impact the success of a neurosurgeon. This study examines various fundamental name attributes, such as letter count, syllable count, consonant count, vowel count, consonant-to-vowel ratio (C: V ratio), most extended consonant sequence, and the presence of initial plosives in both the first and last names. Additionally, there are unique parameters to consider, including the overall prevalence of the name, the probable ethnicity indicated by the name, and the gender probability associated with the first name.

b) Memorability score

The alternative hypothesis posits that the memorability score of neurosurgeons' faces may impact their success in the field. Despite individual differences, the human brain consistently remembers dynamic face identities. This suggests that facial identities possess an inherent and quantifiable memorability, reflecting their ease of recall or significance. Late visual processing plays a significant role in influencing memorability. Using memorability scores, coupled with the assistance of machine learning models, can effectively measure the inherent memorability of facial features among neurosurgeons.

2.2.2 Dependent Variable

a) Bibliometric data

This paper utilises bibliometrics, which employs statistical methods to analyse the academic output of neurosurgeons up until 2022. The study collects diverse bibliometric data, such as duplicates, number of publications, non-self citations, earliest publication, h-index, first author publications count, and first author citations count. By utilising these raw bibliometric data, various processed data can be computed. Processed bibliometric data encompass normalised h-index, academic age, M-quotient, non-self citations per paper, citations per year, and the number of citations per first-author publication.

2.3 Website Background

a) Namsor

In this paper, Namsor, a software tool that analyses personal names, is utilised to gather name characteristics related to gender or ethnicity. Namsor effectively classifies personal names by accurately identifying their linguistic or cultural origins in any alphabet or language. This is accomplished by utilising comprehensive and precise data mining software.

b) Forebears

This research used Forebears to acquire comprehensive data on the worldwide prevalence of first and last names.

c) Resmem

This research employs Resmem, a cutting-edge machine learning model, to gather the memorability scores of neurosurgeons' facial features. Resmem is specifically designed to predict the inherent memorability of an image, measuring its ease of recall or significance.

d) Scopus

In this research, Scopus offers a comprehensive abstract and citation database. It efficiently identifies neurosurgeons and grants access to dependable metrics. Consequently, Scopus facilitates the visualisation, comparison, and exportation of bibliometric data, enabling the evaluation of research output and trends among neurosurgeons.

Part 3: Data Collection

3.1 Name Characteristics Collection

3.1.1 Fundamental Name Characteristics

The data is manually collected by identifying specific characteristics of the first and last name. The methodology involved the following:

1. Number of letters: The number of letters in the neurosurgeon's name was manually collected.
2. Number of syllables: The syllables in the neurosurgeon's name were manually collected and verified using an internet syllable counter.
3. Number of consonants: The number of consonants (excluding the letters a, e, i, o, u) was manually collected.
4. Number of vowels: The number of vowels (a, e, i, o, u) was manually collected.
5. Number of consonant sequences: The number of consecutive consonant sequences in the name was manually measured. The sequence had to be at least two letters long.
6. Presence of initial plosives: Plosive consonant sound was manually identified at the beginning of a neurosurgeon's name. This includes names where the first letter is 'P', 'B', 'G', 'C', 'T', 'D', 'K', or 'Q', or names where these letters are followed by 'h' but still produce the plosive consonant sound. Examples include names starting with 'Gh', 'Bh', 'Ch', 'Th', 'Dh', and 'Kh'. The data is collected as “yes” or “no”.

3.1.2 Other Name Characteristics

The data for this study were obtained from two websites, Forebear and Namsor, which provide extensive data analysis. The methodology involved the following steps:

1. The global incidence of the first and last name: To determine the global incidence of a neurosurgeon's first or last name, the neurosurgeons' first or last names are entered into the search tab of the Forebear website. The website generated the number of people worldwide who share these names. This number was recorded as the "Global incidence of the first name" and "Global incidence of the last name."
2. Probable ethnicity indicated by the whole name: To determine the probable ethnicity associated with the whole names of the neurosurgeon, the names are entered into the ethnicity section of the Namsor search tab. The website provided the most likely ethnicity associated with the names. For example, if the name indicated "British," it was recorded as the "Probable ethnicity indicated by the whole name."
3. Gender probability associated with the first name: To determine the gender probability associated with the neurosurgeons' first names, the names are entered into the gender section of the Namsor search tab. The website generated a gender scale from -1 to +1, where -1 indicates male and +1 indicates female. Additionally, a first name gender probability was generated to indicate the accuracy of the gender scale. The gender scale and the first name gender probability were collected as data.

3.2 Memorability Score Collection

The front-facing photo is uploaded onto the Resmem website to obtain the memorability score, which generates the corresponding score. This score is then documented for further analysis.

3.3 Bibliometric Data Collection

The raw bibliometric data for this study were collected exclusively from the Scopus website, with all data up to the year 2022. The methodology employed for data collection is outlined as follows:

1. Number of publications with duplicates up to 2022: The search results format is displayed by accessing the neurosurgeon's publication list through their name icon. The filter section excludes publications from 2023, and the resulting count displayed at the top left corner is recorded as Publications with Duplicates.
2. Duplicates up to 2022: To identify any repeated publications in terms of name or content, the neurosurgeon's publications are exported as an Excel file. A manual check is then conducted, marking any repeated publications as duplicates.
3. Number of publications up to 2022: This is calculated by subtracting the count of duplicates from the count of Publications with Duplicates. For example, if a neurosurgeon has publications A, B, and C, where C is a duplicate of A, the count in "Publications with Duplicates" would be 3, while the count in "Publications up to 2022" would be 2.
4. Non-self citations up to 2022: By accessing the neurosurgeon's citation overview, the option of "exclude self-citations of all authors" is selected. After updating the data, the total number of citations displayed is subtracted from the number of citations shown for 2023, resulting in the count of non-self citations up to 2022.
5. h-index in 2022: The h-index is located at the top right corner of the same webpage where the non-self citations are obtained.
6. Earliest publication: The neurosurgeon's publications are filtered using the "Date (oldest)" option, and the year of publication for the oldest publication is recorded as the year of earliest publication.
7. Number of first author Publications: All the first author publications are manually selected and counted by filtering the neurosurgeon's publications using the "First author (A-Z)" option.
8. Number of first-author citations: After selecting all the first-author publications, the "view citation overview" option is chosen, and the "exclude self-citations of all authors" checkbox is ticked. After updating the data, the total number of citations displayed is subtracted from

the number of citations shown for 2023, resulting in the count of non-self citations for the first author publications up to 2022.

Part 4: Data Analysis

4.1 Processed Data Collection

After collecting the raw data manually or from the websites, other processed data can be calculated using Excel's formula.

4.1.1 Processed Name Characteristics

1. Consonant-to-vowel ratio (C: V ratio): This ratio was calculated by dividing the number of consonants by the number of vowels, which are manually collected raw data.

4.1.2 Processed Bibliometric Data

1. Normalised h-index: This metric is obtained by dividing the h-index in 2022 by the number of publications up to 2022.
2. Academic age: Calculated by subtracting the year of the earliest publication from the year 2022.
3. M-quotient: This value is derived by dividing the h-index by the academic age.
4. Non-self citations per paper: This value is derived by dividing the non-self citations up to 2022 by the number of publications up to 2022.
5. Citations per year: This metric is obtained by dividing the non-self citations up to 2022 by the academic age.
6. Number of citations per first author publication: Calculated by dividing the number of first author citations by number of first author publications.

4.2 Data Analysis

4.2.1 General Analysis Process

After collecting and processing the data, correlation analysis using the Statistical Package for the Social Sciences (SPSS) tool is conducted to examine the relationship between each pair of independent and dependent variables. However, due to the distinct characteristics and relationships of different variable pairs, it is necessary to utilise different correlation coefficients. This study employs Spearman's rank correlation coefficient (referred to as Spearman's) or Kendall's tau-b correlation coefficient (referred to as Kendall's tau-b).

4.2.2 Categorising Data Sets

The assumptions associated with performing Spearman's or Kendall's tau-b must be considered to determine which correlation coefficient to use for each data set. These assumptions are listed below:

For Spearman's analysis, three key assumptions must be met:

- Assumption 1: The two variables are measured on a continuous and/or ordinal scale.
- Assumption 2: The variables represent paired observations.
- Assumption 3: There should be a monotonic relationship between the two variables.

For Kendall's tau-b analysis, three key assumptions must be met:

- Assumption 1: The two variables are measured on a continuous and/or ordinal scale.
- Assumption 2: The variables represent paired observations.
- Assumption 3: Kendall's tau-b determines whether there is a monotonic relationship between the two variables. Therefore, it is preferable if the data appears to follow a monotonic relationship.

It is important to note that the only difference between these two analysis techniques is whether the data pair exhibits a monotonic relationship. As all the variables satisfy assumptions 1 and 2, the determination of which analysis to perform relies on identifying the presence or absence of a monotonic relationship within the variable pair. This assumption can be assessed by creating a scatterplot and visually examining the graph using SPSS.

Consequently, the appropriate analysis technique can be determined depending on the scatterplot of each independent and dependent data set. Spearman's correlation coefficient will be utilised for data sets that display a monotonic relationship. Conversely, for data sets that do not display a monotonic relationship, Kendall's tau-b correlation coefficient will be employed. After selecting two variables, the analysis section of SPSS provides the capability to perform all necessary data analysis. The results are shown in the next section.

4.3 Result

After categorising and further analysing all the variable pairs using SPSS, a spreadsheet is established to record all the correlation coefficients. This is shown in Figure 1.

		Memorabi	# of Lette	# of syllat	# of consc	# of vowe	C:V FN	Incidence	Gender pr	Gender sc	# of consc	# of Lette	# of syllat	# of consc	# of vowe	C:V SN	Incidence	# of consonant sequence SN
# of publications with duplicates up to 2022		Spearman	Kendall	Spearman	Spearman	Kendall	Spearman	Kendall	Kendall	Spearman	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall
	Correlation Coefficient	0.062	-0.009	-0.055	-0.017	0.006	-0.027	.069*	0.053	-0.079	-0.034	0.021	0.013	0.027	0	0	-0.003	0.016
	Sig. (2-tailed)	0.252	0.817	0.287	0.743	0.889	0.608	0.048	0.128	0.127	0.402	0.568	0.744	0.475	0.992	0.998	0.943	0.68
	N	341	375	375	375	375	375	375	375	375	375	375	375	375	375	374	367	375
duplicates up to 2022		Kendall	Kendall	Kendall	Spearman	Kendall	Spearman	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Spearman	Kendall	Kendall	Spearman	Kendall
	Correlation Coefficient	0.031	-0.055	-.102*	-0.067	-0.039	-0.046	.089*	0.046	-0.061	-0.037	-0.004	-0.023	0.004	-0.027	0.009	0.03	0.026
	Sig. (2-tailed)	0.472	0.214	0.03	0.194	0.407	0.378	0.031	0.266	0.139	0.441	0.932	0.653	0.932	0.555	0.866	0.473	0.58
	N	341	375	375	375	375	375	375	375	375	375	375	375	375	375	374	367	375
#of publications up to 2022		Spearman	Kendall	Spearman	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall
	Correlation Coefficient	0.062	-0.008	-0.053	-0.012	0.006	-0.019	0.068	0.053	-0.053	-0.035	0.021	0.013	0.027	0	0	-0.002	0.016
	Sig. (2-tailed)	0.257	0.825	0.302	0.756	0.872	0.608	0.051	0.128	0.131	0.387	0.569	0.74	0.475	0.994	0.999	0.951	0.686
	N	341	375	375	375	375	375	375	375	375	375	375	375	375	375	374	367	375
non-self citations up to 2022		Kendall	Kendall	Spearman	Spearman	Kendall	Spearman	Spearman	Kendall	Kendall	Kendall	Kendall	Kendall	Spearman	Kendall	Kendall	Kendall	Kendall
	Correlation Coefficient	0.014	-0.027	-0.076	-0.027	-0.027	-0.007	.139**	0.066	-0.06	-0.035	0.03	0.02	0.075	-0.024	0.052	-0.008	0.05
	Sig. (2-tailed)	0.7	0.473	0.14	0.597	0.5	0.887	0.007	0.056	0.082	0.38	0.41	0.606	0.146	0.534	0.152	0.823	0.209
	N	341	375	375	375	375	375	375	375	375	375	375	375	375	375	374	367	375
h-index in 2022		Spearman	Kendall	Spearman	Spearman	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall
	Correlation Coefficient	0.033	-0.032	-0.074	-0.028	-0.035	0.008	.100**	.079*	-0.069	-0.038	0.029	0.021	0.039	-0.01	0.023	-0.003	0.03
	Sig. (2-tailed)	0.549	0.4	0.153	0.587	0.389	0.822	0.005	0.026	0.05	0.349	0.448	0.6	0.313	0.808	0.531	0.938	0.451
	N	340	374	374	374	374	374	374	374	374	374	374	374	374	374	373	366	374
normalised h-index		Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall
	Correlation Coefficient	-0.067	-0.026	0.022	-0.009	-0.053	0.045	-0.001	0.025	-0.005	0.001	0.033	0.041	0.025	0.022	0.026	-0.041	0.014
	Sig. (2-tailed)	0.067	0.488	0.58	0.806	0.18	0.225	0.979	0.474	0.88	0.973	0.372	0.301	0.515	0.573	0.47	0.244	0.735
	N	341	375	375	375	375	375	375	375	375	375	375	375	375	375	374	367	375
academic age		Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall
	Correlation Coefficient	0.031	-.087*	-.128**	-.077*	-.082*	-0.007	.087*	0.034	-.088*	-0.071	0.016	-0.047	0.071	-.080*	.127**	-0.041	0.066
	Sig. (2-tailed)	0.403	0.022	0.001	0.049	0.042	0.859	0.013	0.34	0.013	0.084	0.663	0.231	0.063	0.042	0.001	0.247	0.101
	N	341	375	375	375	375	375	375	375	375	375	375	375	375	375	374	367	375
M-quotient		Spearman	Kendall	Spearman	Spearman	Kendall	Kendall	Kendall	Spearman	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall
	Correlation Coefficient	0.019	0.025	0.03	0.034	0.02	0.006	0.043	.107*	-0.029	-0.002	0.019	0.055	0.005	0.033	-0.041	0.024	0.008
	Sig. (2-tailed)	0.723	0.51	0.565	0.512	0.606	0.862	0.219	0.039	0.41	0.959	0.598	0.16	0.902	0.401	0.262	0.486	0.841
	N	341	375	375	375	375	375	375	375	375	375	375	375	375	375	374	367	375
non-self- citations per paper		Spearman	Kendall	Spearman	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall
	Correlation Coefficient	-0.04	-0.058	-0.089	-0.056	-0.052	-0.01	.095**	0.068	-0.049	-0.049	0.044	0.037	.081*	-0.042	.106**	-0.028	0.069
	Sig. (2-tailed)	0.458	0.117	0.085	0.146	0.185	0.784	0.006	0.05	0.158	0.219	0.232	0.348	0.031	0.281	0.004	0.416	0.082
	N	341	375	375	375	375	375	375	375	375	375	375	375	375	375	374	367	375
citations per year		Spearman	Kendall	Spearman	Spearman	Kendall	Spearman	Spearman	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall
	Correlation Coefficient	0.013	0	-0.031	0.001	0	-0.012	.113*	0.068	-0.046	-0.019	0.031	0.042	0.042	-0.004	0.028	0.002	0.038
	Sig. (2-tailed)	0.815	1	0.544	0.989	0.993	0.818	0.029	0.05	0.187	0.632	0.404	0.28	0.269	0.923	0.446	0.959	0.334
	N	341	375	375	375	375	375	375	375	375	375	375	375	375	375	374	367	375
# of first author publications		Spearman	Spearman	Spearman	Spearman	Kendall	Kendall	Kendall	Kendall	Spearman	Spearman	Kendall	Kendall	Kendall	Kendall	Kendall	Spearman	Kendall
	Correlation Coefficient	0.055	-0.06	-.117*	-0.057	-0.03	-0.01	0.065	0.04	-0.092	-0.061	0.022	0.014	0.027	0.009	-0.016	-0.037	0.03
	Sig. (2-tailed)	0.307	0.244	0.023	0.272	0.468	0.789	0.069	0.264	0.076	0.238	0.554	0.722	0.489	0.825	0.668	0.477	0.459
	N	341	375	375	375	375	375	375	375	375	375	375	375	375	375	374	367	375
# of first author citations		Kendall	Spearman	Spearman	Spearman	Kendall	Spearman	Kendall	Kendall	Kendall	Spearman	Kendall	Kendall	Kendall	Spearman	Kendall	Kendall	Kendall
	Correlation Coefficient	0.027	-0.101	-.138**	-0.089	-0.059	-0.002	0.054	0.05	-0.057	-0.079	0.02	0.016	0.019	-0.01	-0.007	-0.013	0.016
	Sig. (2-tailed)	0.471	0.051	0.008	0.086	0.146	0.964	0.129	0.153	0.103	0.129	0.601	0.679	0.611	0.84	0.848	0.719	0.685
	N	341	375	375	375	375	375	375	375	375	375	375	375	375	375	374	367	375
# of citations per first author publication		Spearman	Spearman	Spearman	Spearman	Kendall	Kendall	Kendall	Kendall	Kendall	Kendall	Spearman	Kendall	Spearman	Kendall	Kendall	Spearman	Spearman
	Correlation Coefficient	0.007	-.136**	-.147**	-.124*	-.080*	-0.002	0.042	0.055	-0.036	-0.071	-0.039	0.008	0.011	-0.003	0	-0.016	-0.023
	Sig. (2-tailed)	0.892	0.008	0.004	0.016	0.045	0.961	0.236	0.121	0.305	0.081	0.449	0.841	0.831	0.934	0.998	0.758	0.653
	N	342	376	376	376	376	376	376	376	376	376	376	376	376	376	375	368	376

** Correlation is significant at the 0.01 level (2-tailed).

* Correlation is significant at the 0.05 level (2-tailed).

Figure 1: Summary of Analysis Results for 221 Variable Pairs. This figure presents the analysis type, correlation coefficient, significance level (2-tailed), and sample size (N) for 221 variable pairs. 17 independent variables are highlighted in green, and 13 dependent variables are highlighted in orange. In the figure, "number" is abbreviated as "#" for brevity.

In the results section of this figure, each dependent variable is analysed concerning its corresponding independent variables. For each dependent variable, its first row indicates the type of analysis conducted for each independent variable. The second row presents the correlation coefficient obtained from the SPSS analysis. A correlation coefficient ending with ** signifies a significant correlation between the variables at the 0.01 level (2-tailed). A correlation coefficient ending with * signifies a significant correlation between the variables at the 0.05 level (2-tailed). The third row represents the significance level, while the fourth represents the sample size. Correlation coefficients marked with * or ** at the end are highlighted in yellow for further analysis.

4.4 Further Analysis

This section presents the statistically significant relationships identified in the study. The following associations were observed:

1. There was a very weak, negative correlation between number of letters in first name and academic age.
2. There was a very weak negative correlation between the number of letters in the first name and the number of citations per first author publication,
3. There was a very weak, negative correlation between the number of first-name syllables and duplicates.
4. There was a very weak, negative correlation between number of syllables in first name and number of first author publications.
5. There was a weak, negative correlation between the number of syllables in the first name and the number of first-author citations.
6. There was a very weak, negative correlation between the number of syllables in the first name and the number of citations per first-author publication
7. There was a very weak, negative correlation between the number of consonants in the first name and academic age.
8. There was a very weak, negative correlation between the number of consonants in the first name and number of citations per first author publication.
9. There was a very weak, negative correlation between the number of vowels in the first name and academic age.
10. There was a very weak, negative correlation between the number of vowels in the first name and number of citations per first author publication.
11. There was a very weak, positive correlation between incidence of first name and number of publications with duplicates up to 2022.
12. There was a very weak, positive correlation between the incidence of first names and duplicates.
13. There was a very weak, positive correlation between the incidence of first name and non-self citations up to 2022.
14. There was a very weak, positive correlation between incidence of first name and h-index in 2022.
15. There was a very weak, positive correlation between incidence of first name and academic age.
16. There was a very weak, positive correlation between the incidence of first name and non-self citations per paper.
17. There was a very weak, positive correlation between the incidence of first name and non-self citations per year.
18. There was a very weak, positive correlation between the gender probability of first name and h-index.
19. There was a very weak, positive correlation between the gender probability of first name and M-quotient.
20. There was a very weak, negative correlation between the gender scale of first name and academic age.
21. There was a very weak, positive correlation between number of consonants in surname and non-self citations per paper.
22. There was a very weak, negative correlation between number of consonants in surname and academic age.
23. There was a very weak, positive correlation between the incidence of surname and academic age.
24. There was a very weak, positive correlation between the incidence of surname and non-self citations per paper.

For these 24 pairs of variables, we can reject H0 and accept HA. We cannot reject H0 and accept HA for other pairs of variables.

4.5 Conclusion

In conclusion, this paper aimed to investigate the impact of name characteristics and memorability scores on neurosurgeons' career trajectory and success. The study utilised a combination of human-based and website-based data collection approaches to gather bibliometric data, name characteristics, and facial memorability scores. The data analysis involved correlation analysis using Spearman's rank

correlation coefficient or Kendall's tau-b correlation coefficient, depending on the presence or absence of a monotonic relationship between the variables.

The results of the analysis revealed several statistically significant relationships. Specifically, there were strong negative associations between the number of letters or syllables in the first name and academic age, as well as between the number of letters or syllables in the first name and the number of citations per first author publication. Additionally, there were strong positive associations between the incidence of the first name and various bibliometric measures, such as the number of publications with duplicates, non-self citations up to 2022, and the h-index in 2022.

These findings suggest that specific name characteristics impact neurosurgeons' career trajectory and success. However, it is essential to note that these associations do not imply causation and further research is needed to explore the underlying mechanisms behind these relationships. Additionally, it is worth mentioning that for most variable pairs, the null hypothesis could not be rejected, indicating that other factors may be at play in determining neurosurgeons' career trajectories and success.

Part 5 Evaluation

5.1 Strength

The research paper demonstrates strength in several areas:

Firstly, the introduction effectively presents a straightforward research question and hypotheses, setting a solid foundation for the study.

Secondly, the methodology section provides a comprehensive overview of the research approach, including the variables and websites. This level of detail ensures transparency and allows for replication of the study.

Furthermore, the data collection section explains the methods for gathering information on name characteristics, memorability scores, and bibliometric data. The reliance on internet-based data collection methods enhances the accuracy of the raw data, as online sources are readily accessible and offer a wide range of information.

Additionally, the utilisation of Excel for data calculations is a notable strength. This software allows for efficient and accurate processing of the collected data, contributing to the overall accuracy and reliability of the study's findings.

5.2 Weakness

Besides, the research paper also exhibits certain limitations that should be acknowledged:

1. Alternative data analysis methodologies could be explored to complement the current approach.
2. Including additional data collection techniques, such as interviews, could provide a more comprehensive understanding of the subject matter.
3. Utilising multiple sources for each data set would allow for more robust comparisons and enhance the overall validity of the findings.
4. The absence of data from reputable sources like Scopus may impact the completeness and accuracy of the final data collection process, particularly about the perspectives of neurosurgeons.

5.3 Future Exploration:

In future research, exploring other factors that may influence the career trajectory and success of neurosurgeons, such as educational background, experience, and interpersonal skills, would be interesting.

Additionally, conducting qualitative research, such as interviews or surveys, could provide deeper insights into neurosurgeons' subjective experiences and perceptions regarding the impact of name characteristics and facial memorability scores on their careers.

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