

RESEARCH ARTICLE

Twitter Followers Biased to Astrological Charts of Celebrities

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Abstract—Astronomical relationships at the birth times of a practical subset of the top 1,000 most popular Twitter users indicate that an ancient prediction for identifying strength in “followers” for the subset is indeed markedly likelier as the number of Twitter followers increases. Using publicly accessible data, it is shown that the incidence of this astronomical relationship at birth is higher than expected among these Twitter celebrities by using a Monte Carlo simulation, and that a strong positive correlation exists between these Twitter celebrities’ follower numbers and incidence of this astronomical relationship in their birth charts. Within the top 500 Twitter users, the regression relation is similar, but even more acute. Finally, we confirm that Twitter ranking joins many other phenomena in Nature by following the Zipf–Mandelbrot law.

Introduction

Celebrities engage our imagination, our curiosity, and our attention. We follow their words, actions, and even their fashions (James 1993). Very recent developments in social media have allowed us to obtain metrics for the first time of the magnitude of a person’s followers (Twitter 2013).

In this study, we demonstrate that the number of Twitter followers among the well-documented most popular Twitter celebrities is correlated to an astronomical factor based on the celebrities’ times and places of birth, a factor that for millennia has been a signature for a person’s ability to attract “followers.”

This signature is from the ancient system of *Jyotisha Shastra* (Jyotisha) developed in India and now increasingly popular globally. Jyotisha has an extensive literature from astronomical texts to texts giving sets of rules for predicting human, mundane, and meteorological phenomena based on the output from astronomical computations.

If such rules have any validity, then they should be able to be subjected to tests. One example is that a greater incidence of Mars found in certain angles to the Ascendant in the birth charts of well-known athletes has been observed, but in an environment of some debate (Ertel & Irving 2000). While that is partially an empirical observation and partially related to certain theories, our article restricts itself to testing a Jyotisha rule per se.

This article arose from an initially tongue-in-cheek investigation of a rule concerning “followers” and Twitter. Normally, it is very difficult to find a numerical assessment of someone’s following. Politicians are subject to polling, but these results are notoriously fickle and may not represent a genuine following of the person. The emergence of Twitter has provided a numerically assessable following for subscribers. An investigation of this following and the application of the Jyotisha rules to estimate components of the birth charts of Twitter celebrities based on their follower numbers is made here using publicly accessible data and standard statistical methods (Harrell 2001).

Methods

Jyotisha includes the luminaries (the Sun and the Moon), the five planets visible to the naked eye, and the two nodes of the Moon. These are referred to as grahas. In the scheme investigated here, defined in Jaimini Maharishi’s *Upadesa Sutras* (MJUS) (Rath 2002), the South node of the Moon is omitted and the remaining grahas are assessed for the geocentric longitude (longitude) and degree advanced within the sidereal sign in which they are placed. The sidereal zodiac was defined by a committee of the government of India led by N. C. Lahiri and defines the starting point of Libra as the longitude of the star Spica based primarily on *The Surya Siddhanta, a Textbook of Hindu Astronomy* (Burgess 2002).

In the sidereal zodiac, there are twelve signs, each of 30 degrees. Each sign occupies a house fully. In the described computations herein, a ‘house’ is identical to a sign except that houses are numbered starting from the sign rising on the east, which is designated as house number one. Quadrant or ‘kendra’ houses are those at right angles to each other.

The graha positions at the time of birth are sorted by degree except that the North node degree is subtracted from 30 due to its mean retrograde motion. The graha with the highest degree is designated the *AtmaKaraka* (AK), and that with the sixth highest degree is called the *PutraKaraka* (PK). Since the AK refers to the self and the PK for celebrities refers to the collection of followers, the strength of the following is claimed to be related to their mutual relationship. MJUS defines this relationship as strongest when the two are in mutual angles (*kendra*). For example, if the AK is in

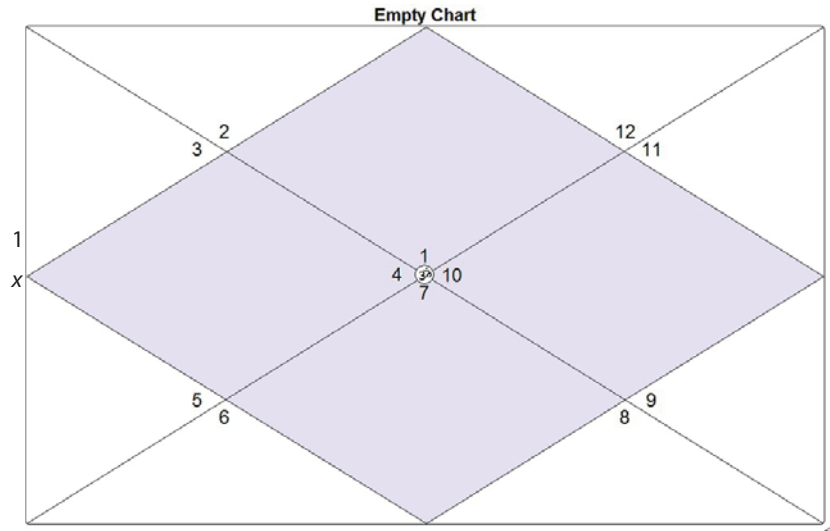


Figure 1. Kendra houses with respect to the top middle diamond are shaded in an empty chart.

the sign of Aries, then the kendras are the houses where Cancer, Libra, Capricorn, and Aries itself are placed. That is, the kendras are always 1, 4, 7, or 10 signs/houses away from each other (Crane 1997). The standard direction in which to count is counterclockwise.

Jyotisha prescribes many different “charts” or diagrams for placement of the grahas. The main ones are the *rashi* (D-1), which is the astronomically observed placements, and the *navamsha* (D-9), which is a subchart constructed by dividing each sign into nine parts, each of which is then assigned the name of a sign in consecutive order running continuously.

In Figure 1, we see the twelve houses in an empty geocentric sidereal Vedic chart. Each section denotes a house (and sign) and is labeled from one to twelve. Houses one, four, seven, and ten are the kendra houses with respect to the top middle diamond (house one) and are shaded. In the subsequent diagrams, the very smallest numbering refers to the actual sidereal zodiac sign in each house as the house itself is invariably defined by the position in the diagram, the first house being always top central.

As an example, we selected the top ranking celebrity at the time of our Twitter snapshot. Figure 2 is the D-1 of Justin Bieber (birth information: March 1, 1994, 00:56 a.m., London, Ontario, Canada; B Rodden rating) and Figure 3 is his D-9. We see that the AK is Mercury (noted as Me) and PK is Saturn (noted as Sa). A kendra relationship is seen in the D-9 but not in the D-1.

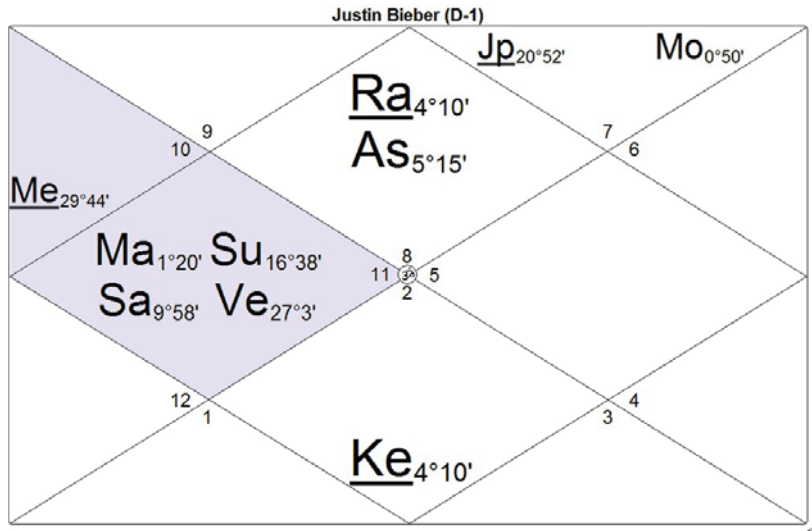


Figure 2. The rashi chart (D-1) of Justin Bieber. The PK is inclusively two houses away from the AK.

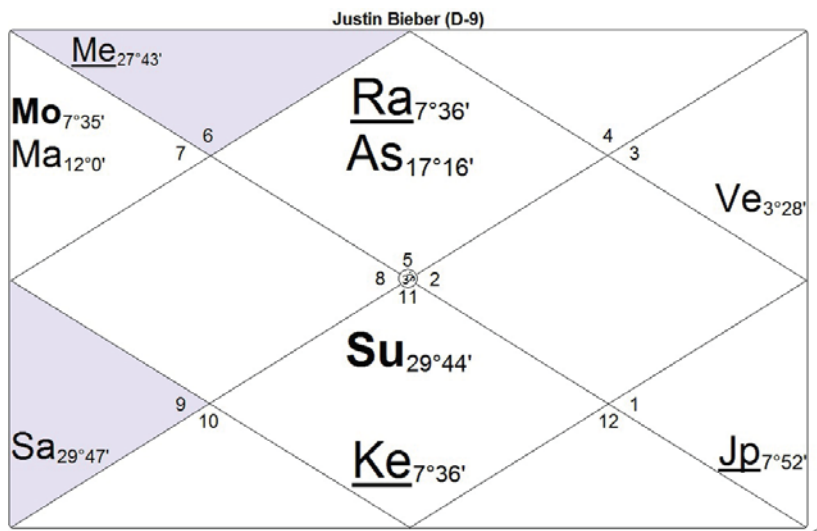


Figure 3. The navamsha chart (D-9) of Justin Bieber. The PK is inclusively four houses away from the AK. Hence, the AK and the PK are in a kendra relationship.

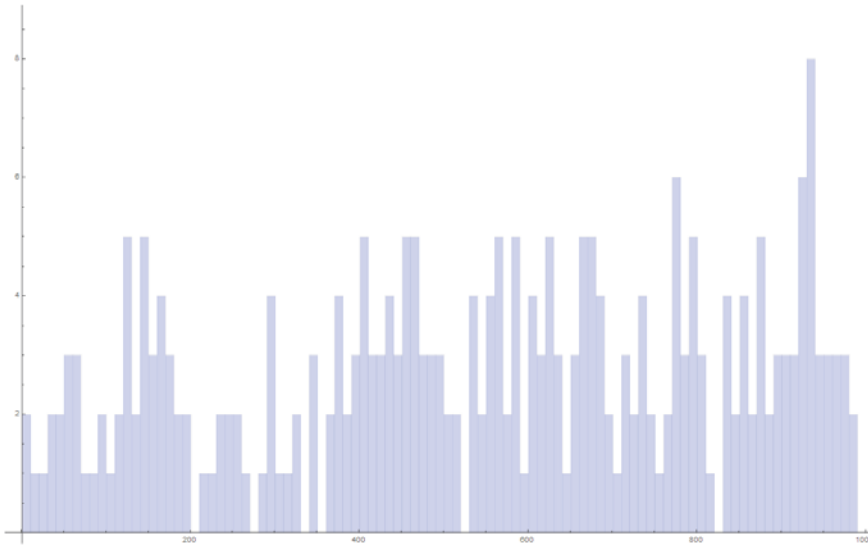


Figure 4. The distribution of 268 observed business accounts throughout the top 1,000 Twitter users. Each bar represents a ranking set of 10.

The list of the top 1,000 most popular users of Twitter on July 14, 2013, at approximately 3:20 p.m., Mountain Standard Time, USA, was captured by screenshots of the list given at <http://twitaholic.com> at that moment. Also provided on that site at that time were the users' rankings and the total number of followers per user.

There were 268 business users (such as CNN), which were excluded. These were spread out fairly uniformly across the rankings (see Figure 4.) The birth time, date, and place (which give us the chart) for each human user in the list was sought from <http://astro.com>. We excluded charts that were of poor accuracy (X, DD, D, or C Rodden ratings) and kept those of high AA, A, or B Rodden ratings (Astro-Databank 2013). The Rodden rating system was developed to facilitate research. The accuracy of birth date and time for many thousands of persons, some famous, were assessed by the editors using standardized criteria. The standards range from the time on a birth certificate (AA), a direct quote from the celebrity (A), or from a biographer (B), etc. Ratings of B and above are thus reasonably reliable, and only and all those Twitter celebrities with B or greater ratings were used. Ensuring that we have good quality data was of top priority and is the main reason that so many birth charts were dismissed.

There may also be some professional bias in the birth information that

is made available by astro.com. However, as those who collected the data are not involved with Jyotisha to any significant extent and are unlikely to have even heard of the obscure rule we investigate, any effect can be reasonably neglected.

For various cultural reasons, this database (Astro-Databank 2013) may not provide a representative sampling of the broad expanse of demographics of the top 1,000 Twitter users. However, our experimental design is intended to provide a robust approach for investigating the group of users for which we could obtain data.

In this way, we created a group of 84 Twitter Celebrity Charts, or the TCC group. The astrological software Shri Jyoti Star (Foss 2013) was used to create the users' charts in the Jyotisha system, using the standard Lahiri ayanamsa and mean nodes, these being the most common choices among Jyotisha scholars. We observed the number of houses from the AtmaKarak to the PutraKarak in both the rashi chart (D-1) and navamsha chart (D-9) for each person. Each chart was scored 1 if a kendra relationship was found. Otherwise, it was scored 0.

For the purpose of comparison, a Monte Carlo approach was employed. In order to generate a chart, the birth time, date, and place were required. Following the steps of bootstrap resampling, the data from the TCC group were used by random selection to generate Monte Carlo sets, each of 84 synthetic charts. This technique overcomes many issues related to selecting a comparison population. For example, as Jupiter and Saturn move slowly, a particular angular relationship might be more common in the TCC group than in an unrelated comparison group. Also, people in general are not born at random times of the day or week or even season (Centers for Disease Control 1999, Goodman, Nelson, & Maciosek 2005). The geographic distribution is also highly skewed in the TCC.

A Monte Carlo simulation through bootstrap resampling satisfies many of these concerns (Efron 1979). It tells us that the elements of data of the 84 Twitter celebrities for birth year, birth month, birth day, and birthplace in random permutations can be used as a sample space for the general population from which the initial sample of 84 comes, however mysterious that general population may be. In other words, the only exactly nontilted dataset to build from the complex distributions of the values given in the births of the 84 celebrities is one expanded from that dataset itself.

This is sensible. For example, many of the celebrities were born in the Los Angeles, California, USA, area. You would want the sample space to be also drawn from theoretical births in the Los Angeles area in the same proportion. Similarly, 1962 was a high time for the year in which our Twitter celebrities were born. That year should be weighted to have more

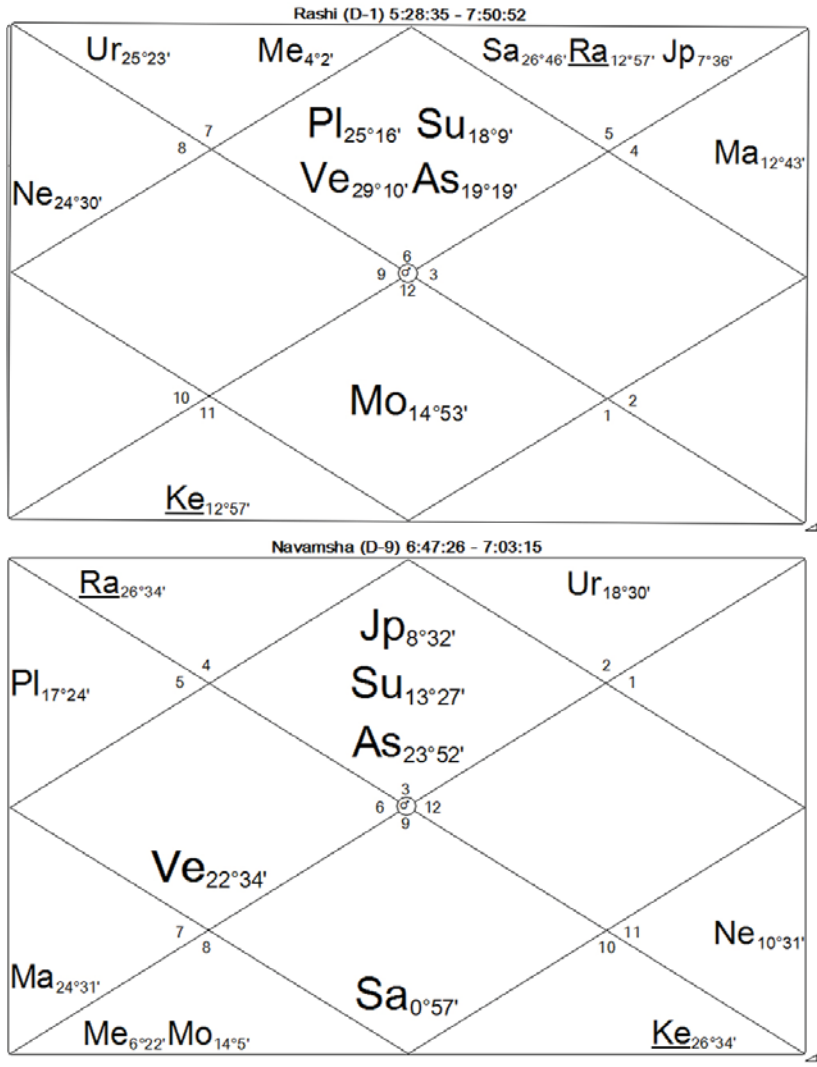


Figure 5. Random chart from the Monte Carlo set. Time is 7:00 a.m.

representatives in our simulated births, and so on. The only major concern that is not answered by this technique is the drops in weekend births, induced and elective (Lerchl & Reinhard 2008).

We found 84 Twitter users among the top 1,000 whose birth data is presented by astro.com with high accuracy. These 84 users are considered celebrities, but the more than 4 billion fictitious people represented by the

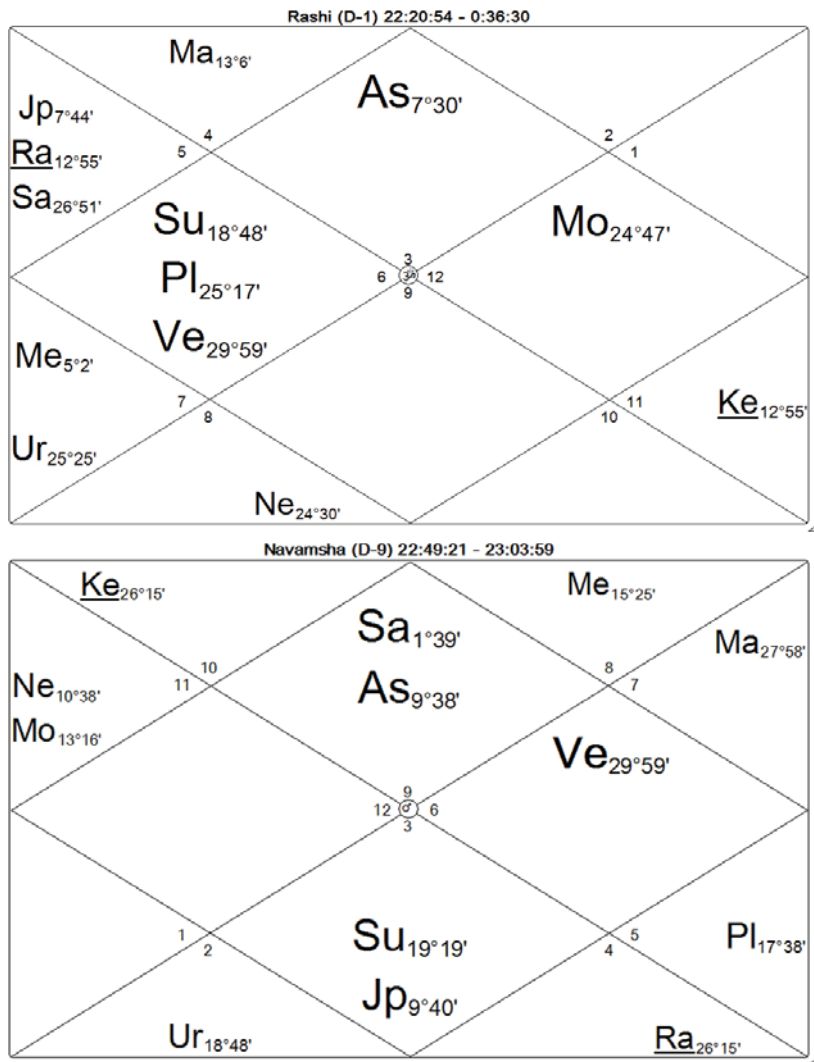


Figure 6. The same number of houses between AK (Venus) and PK (Mars) occur as in Figure 5 even though the time is 10:54 p.m.

84⁵ permutations of their birth days, months, years, times, and places do not have to be, and it is this larger population that we wish to sample.

In order to determine an adequate sample set in groups of 84 synthetic charts and to ensure low probabilities of both type I and type II errors, we generated sample sets, monitoring mean, until $\alpha < 0.05$ and power or $1 - \beta > 0.90$, where α is the probability of a Type I error (a false positive) for

the TCC group incidence and β is the probability of a Type II error (a false negative) (Faul, Erdfelder, Lang, & Buchner 2007). This gave us 65 sets of 84 charts per set for a total of 5,460 synthetic charts.

There are some difficulties with constructing random charts in this manner. 1) A birth date of 29, 30, or 31 will not match with a birth month containing fewer than that number of days. If such a month and date were co-generated, we rejected that combination and chose a replacement entry. This occurred 61 times in creating 5,460 charts. 2) Pennsylvania and Illinois had periods where some hospitals applied daylight saving time and some did not. In these cases, we followed the state law at that time. 3) The Dalai Lama was born in a remote place under Local Mean Time. When this place occurred in a synthetic chart, the nearest place in our atlas was used with the time zone equivalent to the date and place of that chart.

The effect of both of the latter two issues is minimized by the nature of the rule investigated. It seeks a certain coarse angular relationship between two heavenly bodies which remains the same for many hours and is independent of the ascendant.

To demonstrate this principle, a random chart choice from our Monte Carlo sample space is given as an example. The time, date, and place are October 5, 1979, at 7 a.m. in Inglewood, California, USA. The AK is Venus, and the PK is Mars. There are eleven houses between the AK and the PK inclusively in the D-1 and two houses between them in the D-9. These numerical relationships are maintained throughout most of the day, from 3:23 a.m. to 10:54 p.m. in this particular case. See Figure 5 and Figure 6 for the comparison D-1 and D-9 charts at 7:00 a.m. and 10:54 p.m., respectively, on that day at that place.

Hypotheses

Hypothesis One

H1₀ (Null): The incidence for kendra between AK and PK in either the D-1 or D-9 for the Twitter Celebrity Charts are close enough to the incidence in the Monte Carlo chart distribution so that the p-value for the celebrity set incidence is greater than α , while $\alpha = 0.05$, and $1 - \beta = 0.90$.

H1_A (Alternative): The incidence of such kendra in the Twitter Celebrity Charts in comparison to the Monte Carlo set results in a p-value that is less than α , while $\alpha = 0.05$, and $1 - \beta = 0.90$.

Hypothesis Two

H2₀ (Null): There does not exist a regression $f(x)$ with a positive slope describing y such that the p-value < 0.05 for the coefficient of x , where x is

number of followers and y is incidence of kendra in either the D-1 or D-9 in the Twitter Celebrity Charts.

H2_A (Alternative): There exists such a regression $f(x)$ whose graph has a positive slope describing y with a p-value for the coefficient of $x < 0.05$.

Explanations

In Hypothesis One, we test whether the incidence of kendra in either the D-1 or D-9 has a significantly different value for our Twitter celebrities than could be expected in the general Monte Carlo group.

In Hypothesis Two, correlation is tested between Twitter follower numbers (x) and kendra incidence in either the D1 or D-9 (y) using a regression function. If there is such a relationship, then the regression function would have a high goodness of fit with the data with respect to x to support the Alternate hypothesis, while a poor fit would support the Null hypothesis. The uniformly positive slope ensures that as the number of followers increases, kendra incidence increases, which is our ultimate goal to demonstrate.

Note that the goal in H2 is one of correlation, not causation.

A substantiating result in Hypothesis Two would *not* allow the prediction of follower numbers based on a person's chart (as tantalizing a prospect as that may be). Rather it would allow quite the opposite: the determination of the likelihood of an earlier astronomical occurrence at the time and place of a person's birth based on the person's follower numbers, especially if those numbers are high. This astronomical occurrence would then be easily verifiable by astronomy or astrology software or an ephemeris, etc.

Results

Distribution of Number of Houses between AtmaKaraka and Putra-Karaka Follows Cultural Prescription in the Twitter Celebrity Charts

As mentioned above, the standard sidereal chart depicts twelve equal houses that represent the circle of the zodiac. It is commonly divided into quadrants. The houses are simply the zodiacal signs. Houses one through three are called the first quadrant, houses four through six are called the second quadrant, houses seven through nine are called the third quadrant, and houses ten through twelve are called the fourth quadrant.

The kendra (houses one, four, seven, or ten) of each quadrant is in general culturally considered the strongest relational influence, followed by the next house, the panapara, also called succedent (houses two, five, eight, or eleven). The next house, the apoklima of a quadrant (three, six, nine, or twelve houses) is considered the least relationship of influence for that

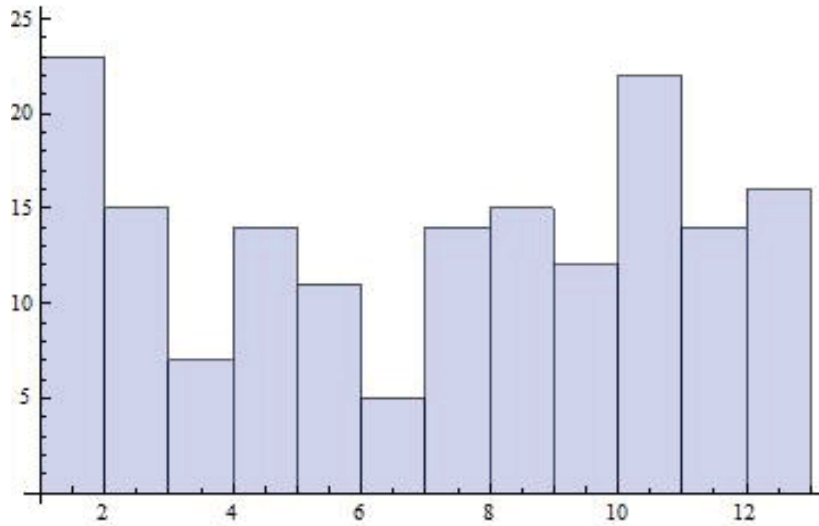


Figure 7. Distribution of total house relationships (D-1 and D-9) between AtmaKaraka and PutraKaraka in the Twitter Celebrity Charts.

quadrant (Rudhyar 1972). Among the kendras, the fourth house relationship is considered the least as it is the “midnight house” to the first. That is, a chart at midnight has the Sun in the fourth house (Rudhyar 1972).

Notice that as demonstrated in Figure 7, these theoretical principles are suggested by the celebrity data. In observed celebrities of the TCC group (Figure 7), for quadrants one and two, the kendra is strongest, the panapara follows, and the apoklima for that quadrant is weakest. For the third and fourth quadrants, the panapara and apoklima are almost equal in results. Of the kendras, the first house is strongest, suggesting that a conjunct relationship between AtmaKaraka and PutraKaraka is the most common kendra relationship for celebrities. The tenth house (conventionally indicating fame) and its quadrant follows closely, then the quadrant belonging to the house opposite the ascendant (the seventh house), and finally last is the midnight house of the fourth, its panapara and its apoklima.

Figure 8 shows by comparison the distribution of houses in the Monte Carlo group. The slight increase in houses one, two, and three is likely explained by the relative proximity of the Sun, Mercury, and Venus. These would be seen in the D-1, and Figure 9 does show the uneven distribution across houses in the D-1 of the Monte Carlo set. Figure 10 shows a relatively even distribution across houses in the D-9 of the Monte Carlo set.

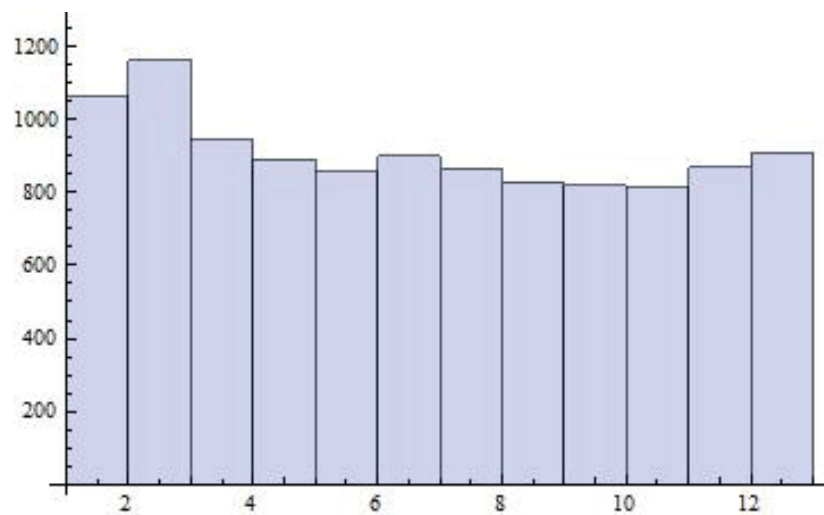


Figure 8. Distribution of total house relationships (D-1 and D-9) between AtmaKaraka and PutraKaraka in the bootstrapped Monte Carlo group.

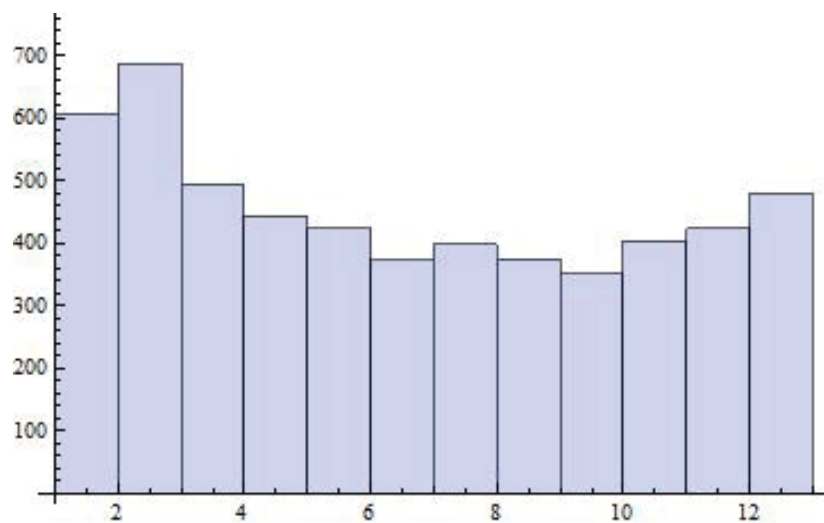


Figure 9. Distribution of house relationships between AtmaKaraka and PutraKaraka in the D-1 only of the bootstrapped Monte Carlo group.

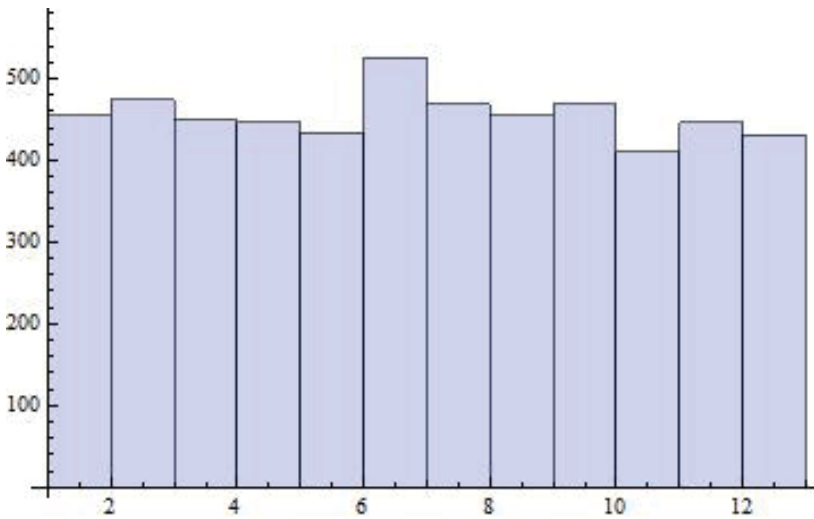


Figure 10. Distribution of house relationships between AtmaKarakas and PutraKarakas in the D-9 only of the bootstrapped Monte Carlo group.

If we compare the two groups for kendra, panapara, and apoklima totals based on the data presented in Figure 7 and Figure 8, there is a significant difference: Pearson's $\chi^2 = 9.38555$, $df = 2$, $p\text{-value} < 0.01$, substantiating the cultural prescription.

These results are an extension to the rule we are testing and are not, as such, directly related to our hypotheses, but are relevant as descriptive information and as interesting and supporting evidence that some ancient astrological principles related to kendra for certain celebrities (i.e. the ones in our TCC group) are indeed showing up in our data. The next two sections directly address Hypotheses One and Two.

Incidence of Kendras between AtmaKarakas and PutraKarakas in Either the D-1 or D-9 for our Twitter Celebrity Charts Is Significantly Higher Than That in the Bootstrapped Monte Carlo Set

We show three methods that satisfy the requirements of $H1_A$. The first method is through a standard normal approximation of the results of kendra incidence in the Monte Carlo set. The second method is through a more precise discrete Fisher's hypergeometric approximation which also provides a better fit. The third is Fisher's exact test.

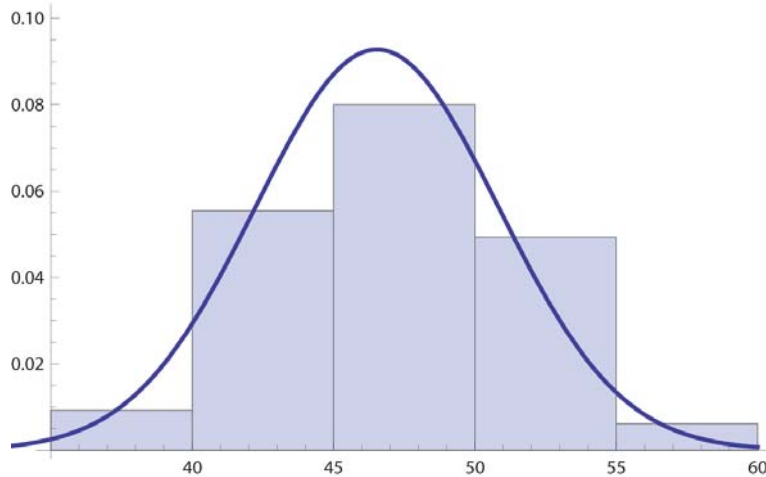


Figure 11. Best fit normal approximation of the Monte Carlo group.

Figure 11 shows the Monte Carlo set data with its best fit normal curve. Table 1 shows the property values for this normal approximation of the Monte Carlo set and the incidence of 60 kendras out of 84 found in the TCC group.

Figure 12 shows the Monte Carlo set data with its best fit hypergeometric discrete distribution. Table 2 shows the property values for the hypergeometric approximation with an incidence of 60 out of 84 (a proportion of 0.714286) found in the Twitter celebrity set and 3,025 out of 5,460 (a proportion of 0.554029) found in the bootstrapped Monte Carlo set.

TABLE 1
Property Values of the Best Fit Normal Approximation

Property	Value
Pearson's χ^2 p-value	0.695358
Mean of the Monte Carlo set	46.5385
Standard deviation of the Monte Carlo set	4.33401
z-score of celebrity incidence	3.10601
One-sided p-value of celebrity incidence	0.000948136
Post hoc actual α	0.0442110
Post hoc achieved $1 - \beta$	0.9115779

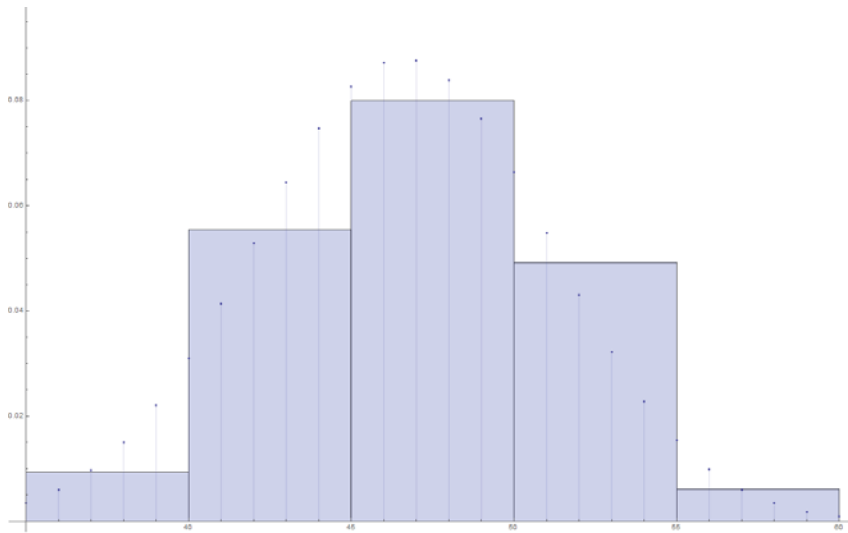


Figure 12. Best fit hypergeometric approximation of the Monte Carlo group.

In both types of best fit approximations, the kendra relationship is more common in the TCC group (one-sided p-value $< \alpha/2$), while $1 - \beta > 0.90$.

The Fisher's exact test yields a one-sided p-value for celebrity incidence of 0.00204829, where actual α is 0.0397944 and actual power is 0.9012414.

Therefore, we accept the first hypothesis of $H1_A$: The incidence of a kendra relationship between the AtmaKarakas and the PutraKarakas for our Twitter celebrities in either the D-1 or D-9 is likely to be significantly higher than expected by either approximation of the bootstrapped Monte Carlo set or by the conservative Fisher's exact test.

TABLE 2

Property Values of the Best Fit Hypergeometric Approximation

Property	Value
Pearson's χ^2 p-value	0.851499
Mean of the Monte Carlo set	46.5455
Standard deviation of the Monte Carlo set	4.52142
One-sided p-value of celebrity incidence	0.00177024
Post hoc actual α	0.0397919
Post hoc achieved $1 - \beta$	0.9020865

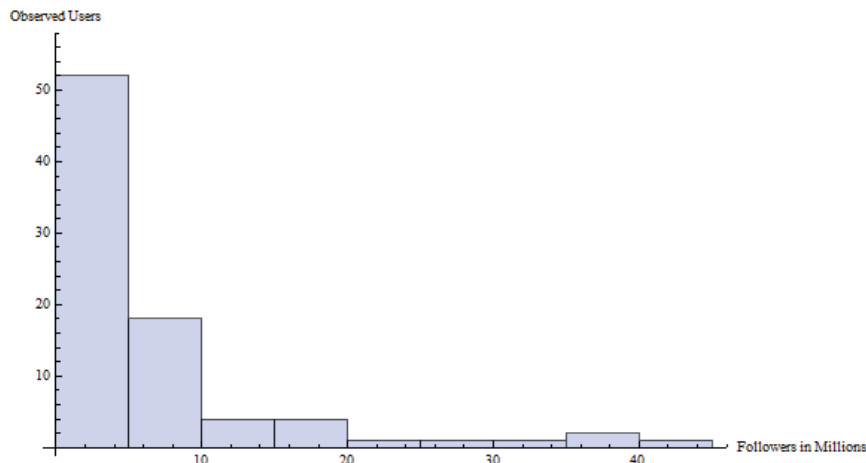


Figure 13. Distribution of number of users (y-axis) in the celebrity group per number of followers (x-axis).

A Positive-Sloped Predictive Relationship between Number of Followers and Incidence of Kendra in Either the D-1 or D-9 Exists in the Twitter Celebrity Charts

Looking at the celebrity dataset, we wanted to test its non-normality with regard to followers so as to select a proper statistical approach to finding the correlation regression function relating followers to kendra incidence. Figure 13 is a distribution chart suggesting an exponential decrease in observed Twitter users as followers increase in the celebrity set. Figure 14 shows a distribution in a probability plot that also suggests non-normality. If the data in the probability plot of Figure 14 were to follow the dotted line, we would know that the data follows a normal distribution. Instead, the curve suggests an exponential quality (Harrell 2001). Such exponential curves have been observed in social media (Faloutsos, Faloutsos, & Faloutsos 1999, Niu & Peng 2013).

Therefore, a nonlinear binary regression method called *probit* was used. The curve of probit regression is highly similar to logistic regression (Harrell 2001). While logistic regression retains descriptive value in the form of an odds ratio and, perhaps, a more easily understandable equation, we would be remiss in using logit (logistic regression) over probit, since probit is a better fit for our data by all measures, including lower AIC (Akaike Information Criterion) and BIC (Bayesian Information Criterion) values as well as lower $-2 \log$ likelihoods and p-values.

The following is the best-fit probit regression equation using x in millions of followers

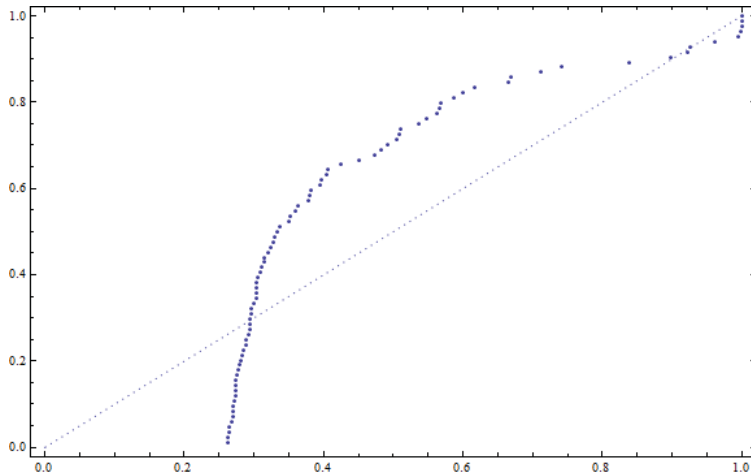


Figure 14. The probability plot of the distribution of followers suggests exponential quality against normality (the dotted line).

$$f(x) = 1/2(1 + erf\left(\frac{-0.101327 + 0.0877916x}{\sqrt{2}}\right)),$$

where $erf(z) = (2/\sqrt{\pi})(\int_0^z e^{-t^2} dt)$.

Figure 15 shows a graph of $f(x)$ in red applied to the dataset in blue. The x-axis shows the number of followers. The y-axis shows either a 1 (for a kendra relationship between the AtmaKaraka and PutraKaraka in either the D-1 or D-9) or 0 (for no such kendra relationship in either the D-1 or D-9) at that level of followers.

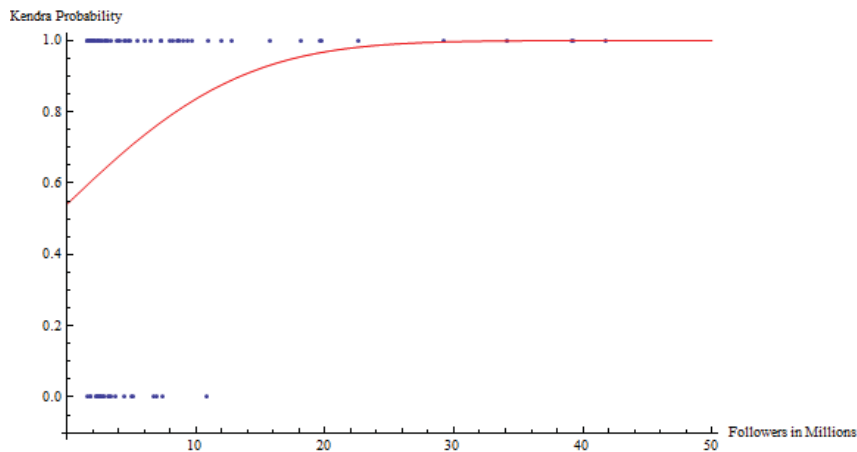


Figure 15. The probit regression equation $f(x)$ in red applied to the dataset in blue.

Table 3 and Table 4 tell us more about the regression parameters and properties. Most of these values are of use in comparing two different models of the same data to see which would be a better match. Note the low-enough p-value that is less than 0.05 for the coefficient of x . The slope of the probit curve is also positive as seen in Figure 16, even as it approaches zero.

TABLE 3
Probit Regression Parameters of $f(x)$ for Top 1,000 Twitter Users

	Estimate	Standard error	z-statistic	p-value
1	0.101327	0.242606	0.417661	0.6761956
x	0.0877916	0.0433124	2.02694	0.0426686

TABLE 4
Probit Regression Properties of $f(x)$ for Top 1,000 Twitter Users

AIC	96.479
BIC	101.341
McFadden Likelihood Ratio Index	0.0798959
Log Likelihood	-46.2395
Likelihood Ratio Statistic	8.03028

In considering the data, we also want to emphasize that the important high tail in Twitter accounts with highest follower numbers is more representative of that whole region than, for example, an equal number of accounts in a middle group. As you can see in Figure 17, Twitter users with the top 10 ranking (each bar represents a group of 10), i.e. those with the very highest follower numbers, are at least twice as likely to have an accurate chart representation on astro.com than any other group. This makes sense. The most popular people are apt to be investigated most thoroughly by writers on astro.com. Thus the important high tail region in the regression relation is likely to be the most representative relatively speaking within the span of celebrity Twitter users on astro.com, even as its represented users are more spread out in terms of follower numbers (see Figure 13). Thus this region is more suited to demonstrating any effect that may be present.

The second hypothesis of $H2_A$ is thus accepted.

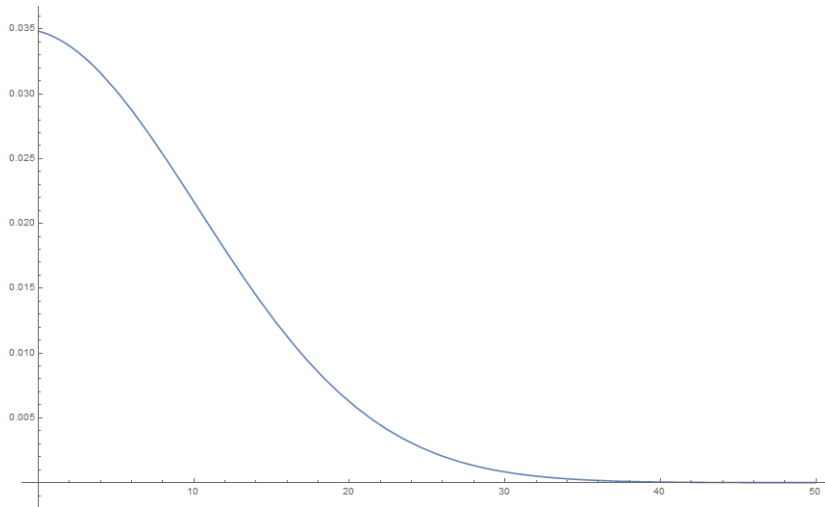


Figure 16. This plot of the derivative of $f(x)$ shows that the slope is always greater than zero.

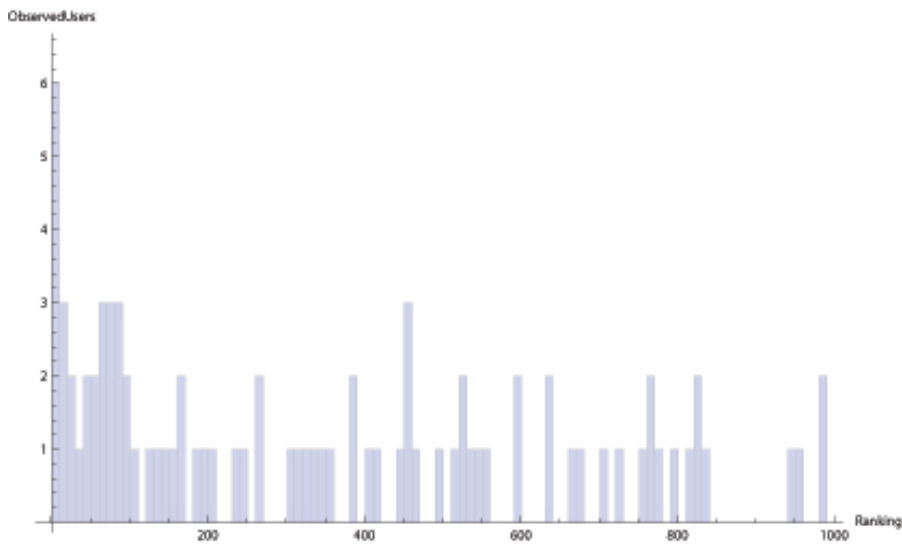


Figure 17. Distribution of number of users (y-axis) in the Twitter Celebrity Charts per ranking level (x-axis).

Sampled within the Top 500 Twitter Users, Kendra Incidence Is Particularly Sensitive and Significant in Correlation to Follower Numbers

Culturally, the search for kendras between AtmaKarakara and PutraKarakara in a chart as a sign of strength in followers is used for only the most popular and successful people. For anyone else, even low-level celebrities, the relationship is said to signify more the person's relationship with his or her children.

Being among the top 500 Twitter users at the moment of data collection, the top 56 of our celebrities were isolated to see if they are particularly subject to this theory of kendra relationship.

Probit regression was also used on this subset of data since p-values, -2 log likelihoods, and AIC and BIC values were lower than for logistic regression here as well. The probit regression equation of $g(x)$ was obtained:

$$g(x) = 1/2(1 + \operatorname{erf}\left(\frac{-0.54886 + 0.168171x}{\sqrt{2}}\right)),$$

where $\operatorname{erf}(z) = (2/\sqrt{\pi})(\int_0^z e^{-t^2} dt)$.

More information on the regression equation can be seen in Table 5 and Table 6. A graph of $g(x)$ is seen in Figure 18 where the x -axis shows the number of followers and is applied to the dataset. The slope is steeper than

TABLE 5
Probit Regression Parameters of $g(x)$ for Top 500 Twitter Users

	Estimate	Standard error	z-statistic	p-value
1	-0.548868	0.420098	-1.30652	0.191375
x	0.168171	0.070756	2.37678	0.0174647

TABLE 6
Probit Regression Properties of $g(x)$ for Top 500 Twitter Users

AIC	60.5573
BIC	64.6434
McFadden Likelihood Ratio Index	0.18585
Log Likelihood	-28.2786
Likelihood Ratio Statistic	12.911

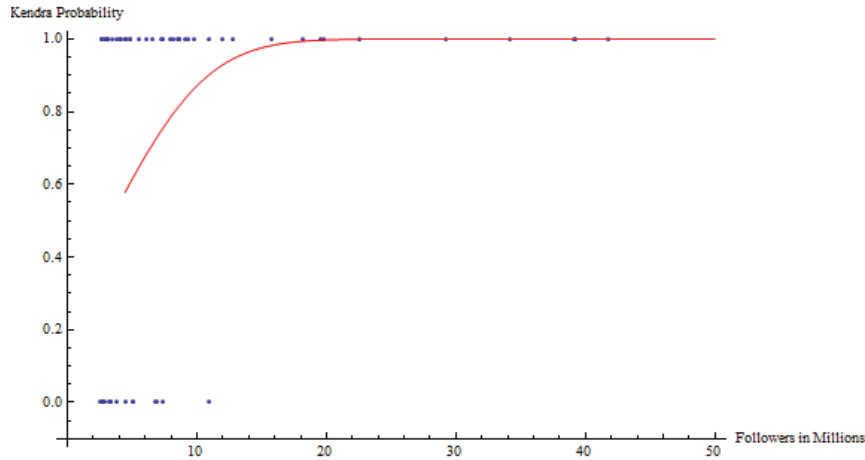


Figure 18. The probit regression equation $g(x)$ in red applied to the dataset in blue.

for $f(x)$, suggesting a higher rate of return of kendra incidence as followers increase in this subgroup. The p-value for the coefficient of x is also less than 0.05 and, as seen in Figure 19, the slope is always positive.

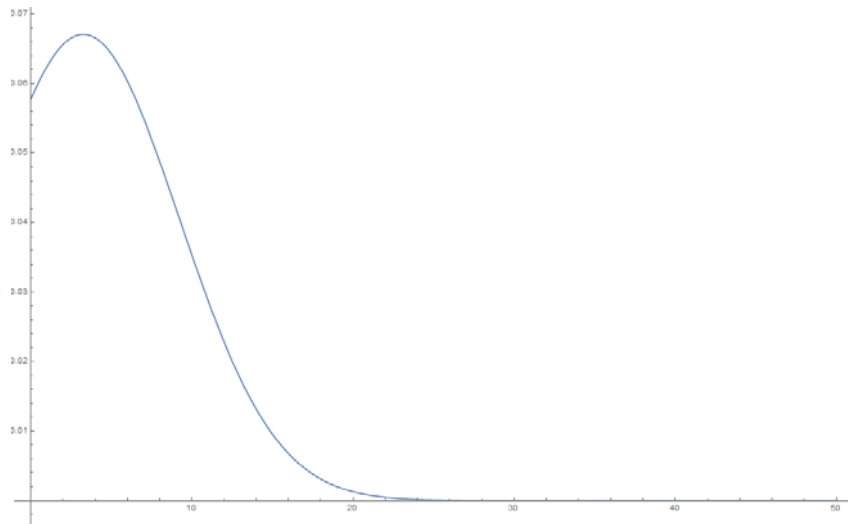


Figure 19. This plot of the derivative of $g(x)$ shows that the slope is always greater than zero.

Remark: Uniform Predictive Relationship for Twitter Ranking as a Function of All Followers Exists

We decided to graph the relationship between ranking and number of followers for the 84 Twitter users whose data we had, considering them a sample of the total top 1,000 users. The following is not immediately related to kendra incidence or astrology.

Refer to Figure 20 and Figure 21. Using standard nonlinear curve fitting, we found that the equation that gives a strong approximation to the relationship between ranking and followers is

$$Ranking(x) = -15.20365 + \frac{631.71567}{x} + (2.9832613 * \sinh(-23.1646477 + 0.3764134 x) / (10^7 x))$$

in which x is the number of followers for a particular user of Twitter.

The implication here is that ranking is not in a haphazardly decreasing relationship to the number of followers. Instead, a precise uniform natural law involving an inverse power, as well as the natural number e (in \sinh), is at work all along the set of sampled Twitter users. Their followers are fulfilling this law.

As seen in Table 7, $p < 0.001$ for all terms, affirming the accuracy of the terms in the relationship as seen in the graph of Figure 21. The R^2 value is 0.999905, affirming a very high confidence of fit.

In fact, the current simple standard model of $c + b/x$ can only achieve an R^2 value of 0.992555. (For a best fit with our data, c would be -121.981 and b would be 1.62665×10^9 . The reader can see the difficulty of relying on such a model by referring to Figure 22 which shows this particular $c + b/x$ best-fit graph.)

TABLE 7
Parameter Table for Ranking as Function of Followers

Term	Standard error	t-statistic	p-value
631.71567	32.6135	19.3698	<0.0001
-15.20365	2.48423	-6.12353	<0.0001
-2.983261×10^{-7}	4.16×10^{-9}	-71.7053	<0.0001
0.3764134	0.0135846	27.7089	<0.0001
-23.16465	5.93425×10^{-10}	-3.90354×10^{10}	<0.0001

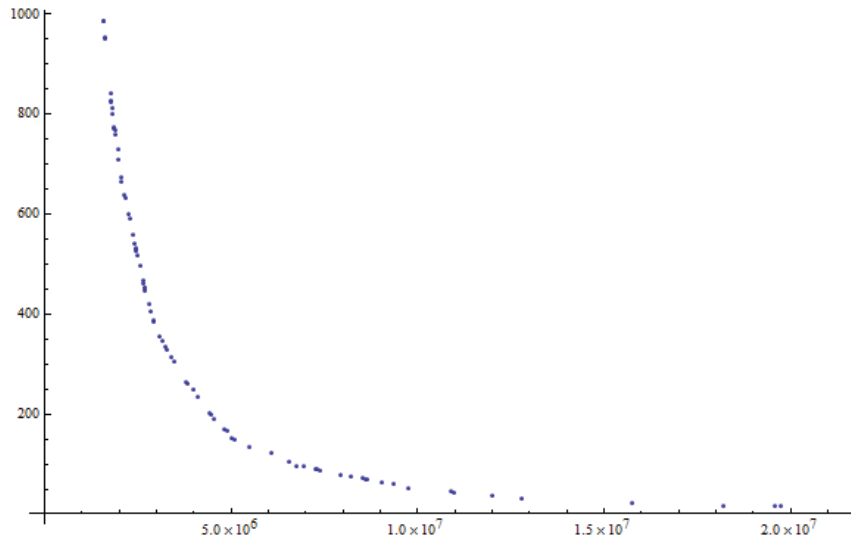


Figure 20. As followers increase (x-axis), the ranking decreases (y-axis).

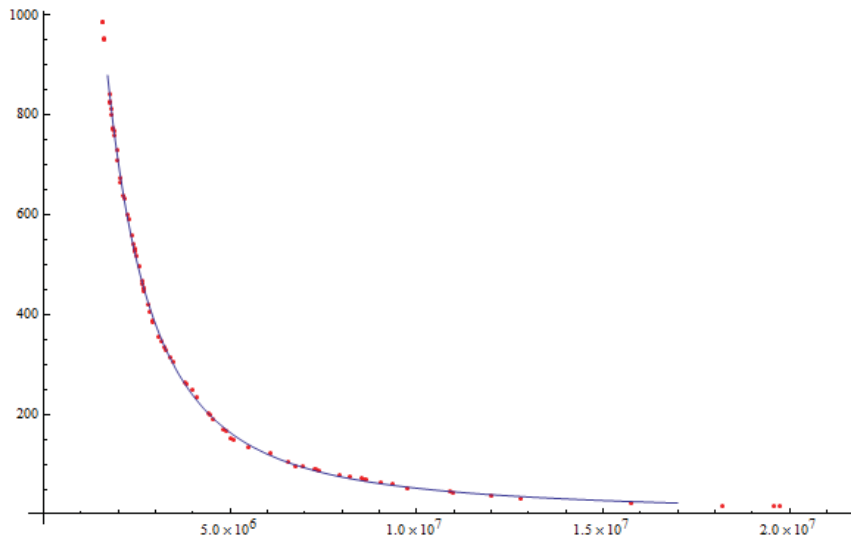


Figure 21. The approximation equation of Ranking (x) in blue is applied to the observed ranking by number of followers, which is in red.

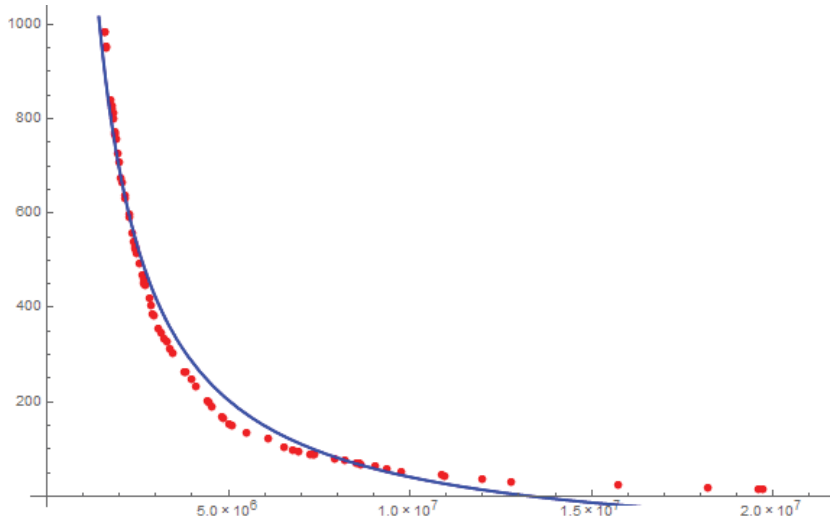


Figure 22. The error of a simple $c + b/x$ best fit model of ranking as a function of followers is demonstrated.

The full nature of the observed data in the Log–Log plot in Figure 23 (including the small curve) verifies that Twitter ranking as a function of followers is yet another remarkable instantiation of the Zipf-Mandelbrot law, joining the relationships in occurrences of words in texts, sizes of cities, abundances of species, and measurements of “pleasing” music, among other examples in Nature (Mandelbrot 1971).

Conclusion

We attempted to demonstrate the force of an ancient astrological prescription for estimating a person’s number of followers. This prescription is a kendra relationship between AtmaKarakā and PutraKarakā in either the D-1 or D-9, an astronomical observation at time and place of birth, which was here determined to be of significance in correlation to number of Twitter followers for a subset of the top 1,000 Twitter users as observed at a moment in time.

The kendra relationships of this prescription are far greater in incidence in either the D-1 or D-9 in our Twitter Celebrity Charts than could be typically expected based on the Monte Carlo distribution, thus satisfying hypothesis $H1_A$. Moreover, kendra incidences in either the D-1 or D-9 in the celebrity set are significantly correlated with number of Twitter followers, increasing as the number of followers increase, satisfying $H2_A$.

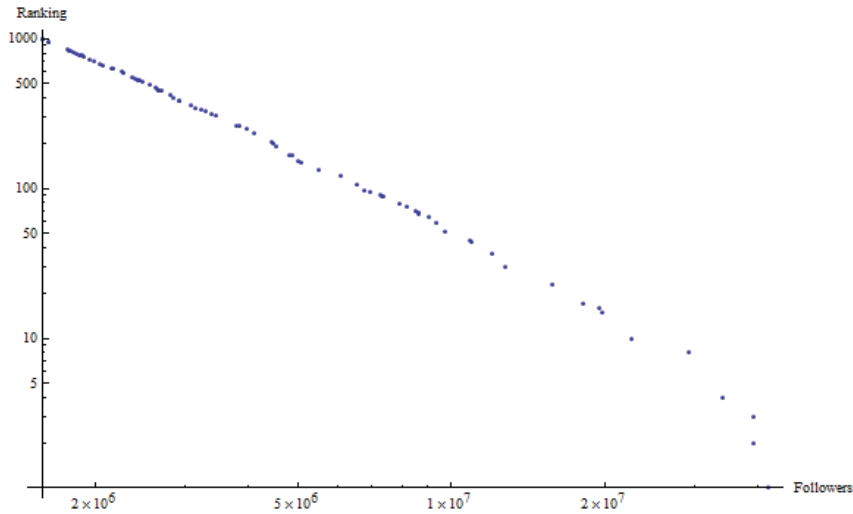


Figure 23. Log-Log plot of observed Twitter ranking over observed number of followers.

We therefore accept both hypotheses and conclude that probability of incidence of kendra relationship between AtmaKaraka and PutraKaraka in either the D-1 or D-9 is high for our Twitter celebrities and becomes higher for the Twitter celebrities with higher follower numbers, especially for celebrities at the very top echelon.

We propose that the validity of cultural Jyotisha astrological maxims should be considered in light of the demonstration in this paper of the prospect of predicting a component of the astronomy at the time and place of a Twitter user's birth based on his or her Twitter follower numbers via the application of Jyotisha rules.

Acknowledgments

Available upon request: Twitaholic.com screen captures; Monte Carlo spreadsheets; Shri Jyoti Star chart list; and Calculations output.

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