A Sentiment Analysis Framework for Estimating Relational Capital

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Abstract: This paper continues research to create a metric for relational capital, a progressively important type of knowledge asset. Knowledge concerning customers and how to engage with them is increasing at an exponential rate in some organizations due to customer relationship management (CRM) and related software gathering customer data. As such, understanding relational capital as a critical piece of an organization's intellectual capital (IC) is ever more important. But measuring the level of relational capital in a firm is difficult. Several consultancies publish brand equity assessments every year (a closely related concept) but these usually only include the biggest and most valuable brands. Popular metrics for studying IC either don't break out the relational capital and other individual components (Tobin's q) or don't include relational along with the others reported (VAIC). In previous work, we've explored using sentiment analysis as a measure of brand value/relational capital, studying the results of a number of firms in several specific applications (consumer brands, tech brands, media brands, etc.). Those results have been interesting but were also only exploratory. At last year's ECKM conference in Lisbon, we received a suggestion that it was time to take some of these metrics and put them together into a brand equity/relational capital predictor. This paper takes that first step, looking at some sentiment analysis results over time and evaluating their relationship with known brand equity estimates. Activity level for brand mentions, variance in activity level, sentiment (positive, negative, neutral), influencer levels, and other potential inputs can be fed into some scenarios for predicting relational capital. The scenarios could include both different variables and different weights, experimenting to determine if an algorithm providing the best fit to the data exists. Once this type of research establishing some benchmarks, additional comprehensive quantitative tests can be conducted in future research, validating and adapting the predictor to different industries and different circumstances. Consequently, we should be able to develop a much better understanding of the role of relational capital and its contribution to firm success as well as ways to help organizations manage it.

Keywords: Intellectual Capital, Relational Capital, Brand Equity, Smartphones, Sentiment Analysis

1. Background/Literature Review

Measuring knowledge assets or intellectual capital is an unsettled issue in our field even after decades of attention. While individual firm estimates and even periodic intellectual capital reports have been produced, with greater or lesser acceptance in terms of methodology, the final step of identifying a generally accepted knowledge metric to establish impact on organizational performance remains elusive. Conceptually and intuitively, the entire discipline believes that superior management of knowledge resources can lead to better financial and other results. But we still lack the means to prove it. And that includes in the area of relational capital.

1.1 Relational Capital

Knowledge management theory suggests that identifying and sharing knowledge resources can lead to competitive advantage (Grant, 1999; Teece, 1998). As tangible assets are ubiquitous and widely available, the potential of intangible assets unique to the firm may be the most available differentiator for many organizations (Nonaka & Takeuchi, 1995). This offshoot of the resource-based view of the firm (Barney, 1991; Wernerfelt, 1984) is the impetus for much of the interest in knowledge management (KM) and related disciplines.

One key related discipline is intellectual capital (IC). If one is to manage knowledge assets more effectively, it helps to be able to identify and measure them. IC grew out of several fields but one was accounting, an attempt to better account for intangible assets such as knowledge. Different approaches, some well-known such as the Balanced Scorecard (Kaplan & Norton, 1992) and the Skandia Navigator (Edvinsson & Malone, 1997), established a basis for later research. That research then generally centered on a framework including human capital, structural capital, and relational capital (Bontis, 1999; Edvinsson & Malone, 1997).

Human capital is most closely associated with KM and was often the core connection between the fields as individual knowledge about job performance is key to both concepts. Structural capital is more about knowledge embedded in the organization, captured in processes and procedures. Essentially, one objective of KM is to turn human capital into structural capital, so it is a key concept in connecting KM and IC. Relational capital, knowledge about interactions with those outside the organization itself (Roos & Roos, 1997), has typically been more of an afterthought. Termed customer capital in some early IC frameworks, it was expanded to include all external publics. Customers, however, do remain the core constituency about which a firm desires knowledge (Gupta & Bhasin, 2014), and with the advent of customer relationship management systems, loyalty programs, customer logins and other advances related to customers and now available big data, the capabilities and value of relational capital have grown considerably in recent years. The volume of information and knowledge has exploded, so the potential value of the asset has similar increased, including relative to other aspects of intellectual capital.

Even with its burgeoning value, relational capital's lack of attention plays out in some of the traditional IC metrics. In firm-specific measures such as the Balanced Scorecard and Skandia Navigator mentioned earlier, indirect measures such as marketing expenditures have some value. But to evaluate a wider number of firms, a relational capital component can be difficult to isolate. Tobin's q (Tobin & Brainard, 1979), for example can be applied in estimating total IC but not the individual parts. Pulic's (2000) relatively popular VAIC method does break out individual components with a direct measure of human capital but then lumps everything else into a structural capital remainder that presumably includes an unidentified relational capital value.

So what is the contemporary view of customer relationships and how we might better measure those to guide knowledge management in organizations? One avenue is to borrow from other disciplines, including the concept of brand equity prominent in the marketing literature. The basic theory of both fields is that ongoing interactions between buyer and seller build relational capital as the seller increasingly learns what satisfies that individual buyer (Sussan, 2012; Stahle & Stahle, 2012). Brands have value because customers trust them, based on previous encounters and experiences, word-of-mouth from other users, and a general sense that the brand knows what to do to make them happy. That comes from learning turned into knowledge, and as the firm/brand can leverage that knowledge across customer service providers, it increases not only brand equity but relational capital (Chang & Tseng, 2005; de Castro, et al., 2004). And, again, in today's world with a wealth of data on customer likes, dislikes, interactions, digital media chatter, and other inputs, that aspect of knowledge management takes on increased importance.

1.2 Brand Equity

Branding is central to modern marketing. In an age of trillion-dollar companies, much of which can come from brand equity, a strong brand is seen as a unique and differentiating business asset. Sometimes misunderstood, brands are not necessarily successful because of the name chosen or from a clever catchphrase but more because, over time, repeated successful interactions with users builds trust. Customers develop expectations about the brand promise and as that is delivered and expectations continuously met or exceeded, the value of the brand increases. High brand values reflect firms with extensive knowledge, gained over time, about customer expectations and how to meet them effectively. As such, brand equity is directly related to relational capital or customer knowledge.

Branding is also an old concept, but in today's world, opportunities for brand building have increased in line with customer data, information and knowledge. Digital interactions with customers have mushroomed, not only online and through social media but also through on-the-ground loyalty programs and online/on-the-ground combinations. These interactions are based on what the literature calls information and communication technologies (ICTs), extended networks with individually identified participants (Lechman, 2017). Browsing behavior, website behavior, transactions, social media, mobile apps, and all sorts of other data-gathering opportunities present themselves and can be attached to known, identifiable customers. This customer data-gathering is one of the key trends driving big data and analytics, illustrating the common definition of big data as the "three V's: volume, velocity, variety (Rothberg & Erickson, 2017). Massive stores of real-time data of all sorts (structured and unstructured) provide opportunities for brand-building and for enhancing relational capital, turning data/information into knowledge/intelligence (Rothberg & Erickson, 2017; Sigala & Chaikiti, 2014; Levy, 2009).

Contemporary branding theory started with Aaker (1991), recognizing the value of a signaling mechanism of a better product worth a premium price. The later idea of brand equity encompassed brand value as a function of awareness, associations, and loyalty (Aaker, 1996). As noted, the value is created over time via successful interactions between brand and customer (Keller, 1993). As interactions differ, the perceived value will be different for different users, but a summation of the extra value across all customers provides the sense of total brand equity (Seggie, et al., 2006; Aliwadi, et al., 2003).

The brand equity estimate is somewhat fuzzy as we generally don't actually have these perceived brand values gathered anywhere nor is there anything resembling brand equity in financial reports or related documents. In some ways, that is where intellectual capital makes a connection as differences between firm value and tangible assets is generally thought to include brand equity somewhere, but not in a manner that can be readily accessed. Were we can obtain brand equity estimates is from consultancies preparing "top brands" lists (Interbrand, 20024), though those are often limited to only the biggest brands and so might be of less use for other firms.

What the growth in ICTs brings to the table are not only the exponential increase in brand-customer interactions but also a better understanding of the impact of those interactions. Data by itself doesn't lead to more brand equity/relational capital, but it can lead to deeper insights into how to further delight the customer, actions that do result in an increase. Existing, longstanding knowledge theory supports this line of thought.

Ackoff (1989) is among those credited with developing the DIKW hierarchy. Raw data (D) can be organization as information (I) from which relationships can be discerned (knowledge, K) capable of then providing deeper insights and understanding (wisdom, W). Substitute intelligence for wisdom, and we have the key contemporary concepts of big data and analytics as they related to our core concept of knowledge. DIKW incorporates all intangible assets of the firm and provides a guide for how they relate to each other and the progression from raw data to actionable intelligence. But the important conclusion is that all parts of the hierarchy can have value, even if not immediately. Knowledge is not the only valuable intangible asset.

Following this line of thought, Snowden's Cynefin framework updates DIKW and removes the hierarchy aspect, seeing data/information not only as inputs for other intellectual capital but as valuable assets in and of themselves (Kurtz & Snowden, 2006). Knowledge is also viewed more broadly, with tacit and explicit knowledge broken out separately and also seen as uniquely present and of value in specific circumstances. As is intelligence, forming a DIKW-like structure running through data/information, explicit knowledge, tacit knowledge, and intelligence (Rothberg & Erickson, 2017). And so decision makers have a range of tools and, with a range of circumstances (complex, chaotic, etc.), the successful strategy will fit the most useful intangible assets to the situation.

This perspective is extremely important in puzzling out the meaning and value of relational capital. As noted, ICTs provide considerable big data to companies with strong customer relationship capabilities. Sometimes that is only data/information, and just having a database concerning customers can be a huge competitive asset—identifying which customers to pay more attention to, tracking behavior and communications, and other data-centric activities can yield strategic advantages. But some organizations also have the ability to learn from the databases, customer preferences, customer reactions to marketing activities, and other such knowledge. Sometimes more tacit (leveraged through personal contact or individual learning), sometimes more explicit (more database-driven, leveraged across IT platforms). And, of course, some firms are able to create predictive, actionable intelligence, with intangible assets being used to find insights about the future help decision-making. The recent explosion of interest in artificial intelligence only adds potential value to this last level of DIKW.

Understanding all of this, contemporary intangible assets related to customers are not only varied and valuable but may contain natural metrics that can be used to assess specific areas of value such as relational capital. The most recent research on brand equity recognizes these possibilities, including incorporating social media metrics as a key input into brand value assessments (Fagundes, et al. 2023) from the academic side. From an applied perspective, the potential for applying social media data in estimating brand value is also gaining favor (McDowell, et. al 2023), especially given the wealth of data and the array of means to analyze them. Including, again, artificial intelligence.

For an individual company, standard metrics such as website visits and behavior, social media interactions, loyalty programs, and similar contacts are routinely tracked and can give a good sense of that firm's specific trends in relational capital. More importantly from a broader perspective, these data can be tracked to assess and compare relational capital across firms. That includes quantitative measures as well as qualitative. User chatter on social media and elsewhere can be brutally honest as well as complementary (Rovai, 2002), but can also provide deeper, more illuminating feedback. And, again, these inputs can reveal true feelings about a brand (Rizun & Kucharska, 2018), and platforms are available to allow gathering of the data and comparisons across companies. As a result, we have new ways to judge relational capital as a concept linked to but separate from brand equity.

2. Methodology

After several studies over the past few years to look at patterns in companies' digital media and how they might relate to relational capital or brand equity, we wanted to take the next step and start lexploring at statistical relationships that might allow identification of the key variables driving relational capital. If those can be determined, then relational capital can be predicted by new metrics, allowing more effective management of this particular aspect of knowledge. Consequently, this is preliminary, exploratory research with the core research objective of uncovering the basic relationships between available digital media metrics and relational capital.

In past studies, topics have included tech brands (Erickson, 2023), media brands (Erickson & Rothberg, 2023), ingredient brands (Erickson, Schmidt & Rothberg, 2020), and major consumer goods brands (Erickson & Rothberg, 2017). Preliminary findings from these small sample exploratory studies were that the more valuable brands tended to have a lot more digital media activity (volume), more neutral and more stable (lower standard deviation) sentiment, higher-rated influencers, and few obvious patterns in terms of platforms or other available variables.

The studies employed Salesforce's Social Studio software (now discontinued though other options are available), allowing "social listening" over designated time periods. Social Studio tracks activity concerning keywords (in this case brands) across the entire web, including social media platforms (X, Facebook), YouTube, blogs, forums, news aggregators and commenters such as Reddit, reviews, and other postings. Results provide data on volume of brand mentions, sentiment (positive/negative), top influencers, country, language, and activity by each digital platform. If one desires the actual posts behind the data, for qualitative research and descriptions (including word clouds), that is also available. Note again, results are from the entire internet, not just owned social media accounts.

For this exercise, we pulled the data from the tech brands study (Erickson, 2023) which included two different time periods of results. The brands included were from the smartphone industry, including high-value brands Apple iPhone and Samsung Galaxy as well as relatively high-value Chinese brand Xiaomi, and lesser-known brands Vivo and Oppo. In addition to the Social Studio data, brand equity estimates were available from Interbrand's (2024, 2023) Best Global Brands report for the Apple, Samsung, and Xiaomi names. The brand equity for Vivo and Oppo would be considerably lower, and we plugged in a number for each midway between Xiaomi's value and zero.

Preliminary variable correlation analytics were run using SAS Viya visual analytics software, allowing rapid comparison of the explanatory value of all statistics and easy variable manipulation of identified candidates for additional testing. Note the results are *very preliminary* as the sample is quite small. But the initial insights can then be applied in wider and more statistically significant manner in future studies.

3. Results and Discussion

Initially, we performed a correlation analysis on each of the available variables in the model. These included:

- Brand equity (dependent variable)
- Volume of digital media activity
- Volume range
- Sentiment (positive)
- Sentiment range
- Influencer index (1-100, higher is more influential)
- Twitter volume
- Twitter range
- YouTube volume
- YouTube range
- Forum volume
- Forum range

While the full correlation matrix was obtained and reviewed, we'll only report on the correlation of each variable to the brand equity value the exercise is meant to estimate. These results are included in Table 1.

As indicated, strong positive correlations are seen with the Volume, Twitter, and, to a lesser degree Influencer variables. The Volume and Influencer results are in line with expectations coming into this analysis. The Twitter result was more surprising. But the initial conclusion is that digital media volume, influential influencers, and Twitter (now X) attention are related to strong relational capital. Strong negative correlations are seen with Sentiment, Twitter range, YouTube range, YouTube volume, and, to a lesser extent, Forum range. This also agrees with previous research indicating high equity brands tend to have less extreme feelings (sentiment) but more steady, neutral reactions. The digital media results were less expected but may also indicate more stability (all three ranges) and less YouTube volume (for no obvious reason).

Table 1: Correlation Results

Variable	Correlation with Brand Equity	Regression	Neural Network
		R^2 = .8908 **ASE** = 2296.3	**ASE** = 0.098
Intercept		-830.62 (.062)	
Volume of digital media activity	0.607	.003 (.206)	
Volume range	0.309	.011 (.198)	
Sentiment (positive)	-0.639	973.5 (.111)	
Sentiment range	-0.138	1205.8 (.152)	
Influencer index (1-100, higher is more influential)	0.398	-1.23 (.018)	
Twitter volume	0.694	330.6 (.118)	
Twitter range	-0.713	-674.8 (.432)	
YouTube volume	-0.498		
YouTube range	-0.516		
Forum volume	-0.239		
Forum range	-0.414		

The table also includes results from a linear regression including the all the variables except the less correlated digital media platforms (YouTube, Forums). Regression adds the ability to see the impact of each variable on the predicted value of brand equity, its statistical significance, and how the explanatory variables work together rather than in isolation.

Before analyzing the regression results, it's important to stress once again that the sample is very small, so any statements about the outcomes in general or statistical significance in particular need to be made with some care. There is not enough data to make confident predictions or to discern fine distinctions. The point of this more exploratory work is to identify potentially interesting variables for future work with bigger, intentional data sets.

Initially, note the results are presented with the coefficient for each item first, with the p value in parentheses. Which also raises a caution about the coefficient as it may be misleading in terms of magnitude and size with relation to the dependent variable—in a complex regression of this sort, with potential between-variable correlations among the many variables, the coefficients would not have the interpretive meaning of a slope in a more simple equation. As a predictive model is refined, we may be able to overcome this aspect in time. But for now, the size and magnitude of the coefficients can't be trusted (collinearity), even if we do include them.

The intercept term is both large and has the second lowest p-value (second highest significance), something that would likely be a concern in a different setting. One typically doesn't want a lot of the equation's explanatory power in the constant. But, again, in a small sample exercise, one can take the result as just part of making the equation work and leave the more rigorous interpretations for future study.

Of the variables, the one with the largest p-value significance is Influencers, at a 98% confidence level. Influencers does have a negative sign for the coefficient but that doesn't match up with what the correlation matrix tells us and makes little intuitive sense. The relative importance of the variable, however, is clear. The next highest p-value significances were Sentiment (positive) and Twitter Volume, at the 89% and 88% levels, respectively. The coefficients both make little intuitive sense, predicting single unit changes in these variables corresponding to hundreds of billions of dollars in valuation, but the Twitter variable at least agrees with the correlation result in sign. That case is similar to what we see with a fourth variable, Sentiment Range, with p-value matching an 85% confidence level but a wacky coefficient value.

The overall quality of the regression is quite good, with an R^2 of .8908, explaining 89% of the variation in brand equity. Average Squared Error (ASE) is also reported, a quality metric of prediction error whose importance will become clear shortly. So, in summary, the regression shows good fit with these variables, even with such a small sample. Moreover, we can identify some key variables that might merit further study, specifically Influencers, Sentiment, Twitter Volume, and Sentiment Range.

A different way to take a preliminary statistical look at the data is to apply an AI approach with a Neural Network. The SAS Viya software performs this analysis easily, grouping the initial variables into new predictors based on iterations to identify the best way to include and weight the inputs for maximum predictive capability. While the underlying relationships are complex and difficult to fully describe, the interactions of the variables uncovered by the analysis can be used to substantially amplify the predictive power. A neural network does provide a straightforward overall quality score and a sense of which variables are most important to the predictive power of the analysis. A visual of what this result looks like within the software is included in Figure 1.

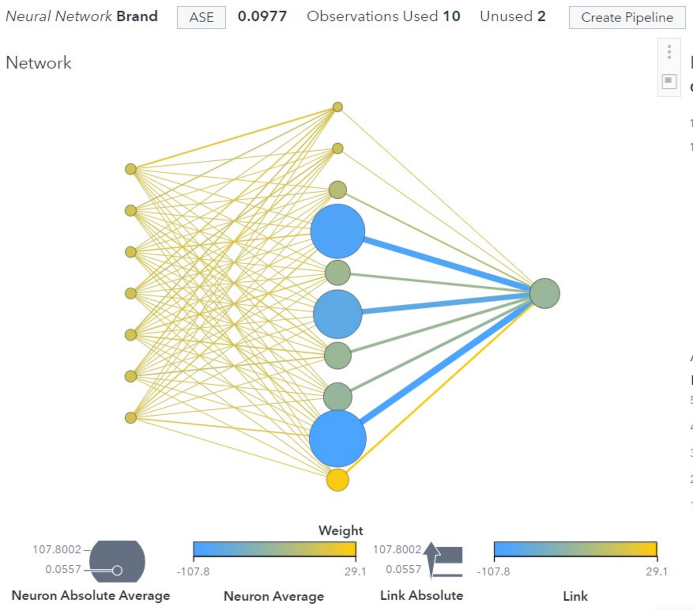

Figure 1: Neural Network Structure

As indicated in the figure, the individual original variables all feed into the newly constructed variables. These latter variables have different levels of correlation with the dependent variable, with the three coded blue showing a strong relationship. Again, we don't know how the original variables specifically fit into these most important constructed variables, but the system has uncovered the manner in which to arrange them and their interconnections in a manner such that the constructed variables have a high degree of predictive power. The quality metric of the overall equation is quite high, an average squared error (ASE) of only 0.0977. Note that figure in relation to the regression ASE of 2296.3, a much lower error rate is obtained with the Neural Network approach.

Further, although we don't have detailed specifics about the relationships between the original variables and the constructed variables, we do have some metrics on relative importance available if we use SAS Viya's Model Comparison feature (Figure 2). While we had already drawn some conclusions from the regression output itself about variable impact, the model comparison shows Influence and Sentiment Range as the most important inputs with all aspects of the process included. These were two of the top four in the discussion above, but the model comparison draws on additional details to isolate the most important contributors. These variables are further validated and even more emphasized in the Neural Network model (note the darker shade of blue). Whatever their relationship with the key constructed variables, these two are the most impactful original variables in a model with high predictability.

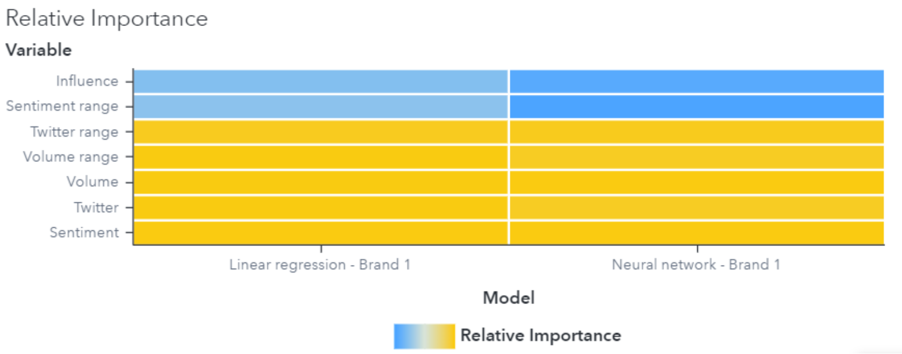

Figure 2: Model Comparison

What we're left with is a much better idea of what the key variables available from sentiment analysis might be, confirmed by a more quantitative approach. Influence, what other widely followed individuals/sites might interact with the brand, and Sentiment Range, how much brand sentiment varies (probably less variation, the higher the brand equity), appear to be the variables on which to focus more research. With more data, bigger sample studies, and other approaches, we can use these initial results to uncover a reliable relational capital metric.

4. Conclusions

This paper reports on initial work to quantify and structure variables that might reliably predict relational capital in organizations. An increasingly important part of firms' intellectual capital holdings, relational capital remains an understudied area in the field.

Using available data on brand equity, a closely related concept to relational capital, we used additional data gathered through the Social Studio sentiment analysis program. Although a very small sample and not statistically reliable in any way, the data are useful to provide initial confidence in concept validity and direction for future research. Previous studies, using data but more qualitative in analysis, had identified some key variables associated with high brand equity/relational capital. These included volume of digital media activity, brand sentiment and sentiment variability, influencers, and, potentially, activity on individual digital platforms.

This analysis used SAS Viya, both regression and neural network modeling, to plug these variables into a more advanced, quantitative analytical framework. The regression results were interesting and surprisingly powerful (high R^2) though the amount of collinearity in the high number of variables limited the ability to make assumptions on individual impact beyond significance. The neural network provided surprisingly impressive results, with a very high level of predictive power. The details of the constructed variables the neural network AI provided are opaque, but their reliability is quite high, with an error rate magnitudes lower than the already high R^2 regression results.

What the indicates is that there is a strong statistical relationship present, apparent even in a model with low statistical reliability. The neural network provides initial guidance to ferreting out this relationship and confirms there is something powerful to be uncovered. A significant, reliable predictive model is apparently available to be found.

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