Media Selection: A Method for Understanding User Choices Among Popular Social Media Platforms

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Abstract. How a person perceives social media platforms should provide insight on the platforms they choose to use or not. Literature reviews highlight studies focused on demographic, familiarity, social influence, application, and usefulness as a means to differentiate choice/use. This study combines quantitative and qualitative techniques to examine Social Media Platform (SMP) preferences.

Using a web-based card sorting application, 59 participants completed an open sort activity on 19 SMPs. Information was also collected on SMP usage, age and gender. The strength of the paired-relationships between SMPs is presented in the form of a similarity matrix and a dendogram (hierarchical cluster analysis). A set of decision rules were developed in order to arrive at 44 standardized categories. A matrix of categories and SMPs provides means to explore associations. These relationships are examined for overlap and absence. This allows researchers to discuss findings in terms of current theory and practice.

Keywords: Pile sort · Media richness theory · Media synchronicity theory · Social media platforms

1 Introduction

Scholars have engaged in many different lines of inquiry in an effort to understand why users adopt certain social media platforms over others. For example, different work has investigated social media with respect to user intentions [1], demographics, and kinds of interactions afforded by different sites [2, 3]. This work, however, seeks to extend and deepen our understanding of user engagement, by getting users to categorize the platforms they use in an effort to understand more about how users think about their interactions with these tools. When combined with simple demographic data on the users and a series of survey questions about social media use, it is hoped that this method can shed light on connections that may or may not be immediately apparent through survey/questionnaire and demographic data alone.

Demographic categories have been considered in the existing literature as predictors of trends in use. For example, Saul discusses an "exodus" of younger users from Facebook [4]. Related work by Chan *et al.* show how gender influences Facebook engagement, with women more likely to (a) have an account and (b) participate more often than

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their male counterparts [5]. Studies by Malone and Kinnear [6] as well as Hagag *et al.* [7] discuss how shared culture or cultural values can influence preferences for a specific website or web platform. Related to the question of demographics are studies of affordances which highlight the motivation for certain segments to use specific online platforms. For example, Bell *et al.* [8] showed how Facebook can help older adults feel less lonely. And Chen showed that women bloggers tend to use social media for the purposes of recreation and information sharing [1]. This is supported by market research showing that new moms tend to be frequent and engaged users of Facebook, since they are able to form a community which helps with information sharing, recreation, and social stimulation [9]. Despite this research, demographics alone does not tell the story of why people engage (or ignore) different social networks, and thus the question tends to be much more complex than which gender, age segment or cultural group a person belongs to, especially when these categories so often intersect.

Moving beyond the demographic question, other factors have been considered in the literature as possible explanations for why certain people use different social media platforms. For example, Correa *et al.*'s work showed that certain traits, namely, openness and extraversion show a positive correlation with social media use (in contrast to traits like emotional stability, which exhibit a negative correlation) [10]. Other studies have shown a relationship between familiarity with a social network (or perceived familiarity) and the likelihood that users would continue to engage with it [11]. Similar research has revealed that convenience and cognitive effort has a simple and direct impact on social network adoption [12]. Other studies have honed in on the relationships between people and corresponding social network influence as a predictor of social network use. Cataldi and Aufaure showed how influence can spread the adoption of a network (or a message along that network) [13]. Palazon *et al.* showed that the willingness of individuals to join brand related pages on sites like Facebook depends on their social network and the influential individuals within that network [14], and Herrerro *et al.* demonstrated how online search behaviour is directly influenced by the social network of the individual doing the searching [15]. This type of behaviour would seem on the surface to confirm an affordances thesis. That is to say, since social media affords a certain type of networked social interaction, social interactions should therefore drive a person's choice of platform and the way they interact on it [16].

Following the extensive body of research on social media use and affordances [2, 17], studies have shown that people often use specific platforms because they offer a certain type of interaction with others. For example, Gomes and Pimentel developed a series of "if-then" rules that describe user behaviors using "data mining procedures." Their results showed that users engaging with each other on Facebook for Blackberry tended to demonstrate reciprocity to the exclusion of other mechanisms of social or collective influence [18]. This is reasonable from an affordances perspective as Facebook.com itself—as well as all other social media—affords posts that demonstrate reciprocity through likes, clicks and shares. But while this work highlights an important user motivation related to social media engagement, the reduction of user behaviors to simple if-then formulas may not take into account all the ways that people choose to interact using these platforms. Rather than simply data mining, it is advisable to understand social media use, or really any human social behaviour with respect to a complex spectrum of deeply contextual and sometimes contradictory human understandings, and motivations [19].

The question of context—who chooses what and why—has thus far received little investigation outside of high-level market or demographic categories. To achieve a contextual and rich analysis of individual motivations for social media use, we recommend that demographics and affordances be considered alongside other cues. For this, it is useful to draw from and expand earlier models of media choice. Building on Media Richness Theory [20], which showed that interlocutors seek out and choose richer media in order to better understand and communicate issues with others, Dennis and Valacich's Media Synchronicity theory tries to build a model that takes into account multiple processes, in this case five: immediacy, symbol variety, parallelism, rehearsability and reprocessability to explain how people choose to engage with a particular medium of communication [21]. This understanding is useful because it supports different user motivations for adopting a particular communication medium and thus can be very useful for understanding motivations for social media use. For example, Chan showed how asynchronicity can motivate shy people to engage with social media platforms like Facebook as a way to experience social interaction in a less threatening context [22]. Similarly, Taipale showed a relationship between demographic social media choices and the synchronicity of the chosen medium or platform of communication–making a link here between demographics, affordances, and media richness that is a step forward in understanding the varied complexity of human motivation [23]. However, media synchronicity theory is still limited as it assumes that media choice is directly related to a conscious goal of communication between two or more individuals, and as such it may not account for some of the less conscious or un-inferred categories of experience. Examples could include social influence, felt but seldom reflected upon group or collective or social-network hierarchies that impact personal preference, personal or group experience or history related to different platforms or assumptions or attitudes about services that defy rational explanation.

Free pile sort has been used in anthropology and sociology in such diverse fields as health care, organizational communication, cultural anthropology, and food studies [24–28]. It is generally used in combination with the collection of demographic data and survey research as a way to reveal taken for granted assumptions or demographic and network relationships not immediately apparent through survey data alone. While it is quite common outside of communication studies, it has not yet been employed extensively to understand computer mediated communication. Its great strength is that it allows for both quantitative data collection, in the sorting and categorization of elements, and qualitative data collection [29] these are then combined to form a detailed explanation of why participants sorted different elements in a specific way. When combined with the demographic details of the participants, it thus has the power to extend an analysis offered through a media synchronicity lens by offering (1) demographics, (2) professed motivation (3) relationships between different media as uncovered through categorization (4) social cues and other less-conscious influences (5) the discovery of other motivations not anticipated by the researcher or research team (in contrast to a survey instrument with pre-determined lines of questioning or scales of answers). The pilot study detailed here, thus employs free pile sort in a new way, that is in the understanding of social media preferences in order to address several hypotheses related to user motivations.

2 Methodology

2.1 Participant Recruitment

Active social media users were recruited through open calls on Reddit and personal connections (LinkedIn, individual emails, etc.). Participants had the option of passing along contact information (snowball effect) but most did not do this. The engagement protocol can be broken down into three parts. We used the Optimal Workshop *OptimalSort* web-based application to collect questionnaire and card sort data.

Pre-Activity Questionnaire – Usage. Participants responded to the questions below. These questions not only allowed the collection of participant data, but also primed participants for the subsequent card sort (equivalent of pile sort) activity.

(a) What social media applications/services are you a registered user of?
(b) What social media applications/services did you use yesterday?
(c) Think about the last three things you posted on any social media service/application. What were they?

Card Sorting Activity. Participants were presented with 19 cards to sort by moving individual cards from a list to an area where cards can be grouped together in clusters (categories). Participants had freedom regarding the arrangement of the cards and the naming of the clusters. This is known as an open card sort and is most commonly used by Information Architects [30].

With 19 cards for our participants to sort, there is a potential for 18 pairs for each card. The higher the frequency that two cards are paired together, the stronger the association. The resulting similarity matrix (Fig. 1) shows the grouping of cards together (%) by the 59 participants.

Post-Activity Questionnaire - Category Grouping, Frequency of Use, Demographics. We asked participants to describe why they ordered the list the way they did, and had them provide answers to some standard demographic and use-pattern questions, including frequency of use, gender, age, and the habits of their offline social or family networks. Importantly, this allowed us to understand the contextual information that helped make sense of the patterns we observed in the free pile sort data.

Grouping Categories – Meta Analysis. Participants in the exercise of sorting and categorizing 19 social media platforms generated 390 categories. The OptimalSort application allows researchers to standardize categories so it is possible to examine individual cluster labels and group them together. We developed the following decision rules in order to get to a reasonable number of standardized categories.

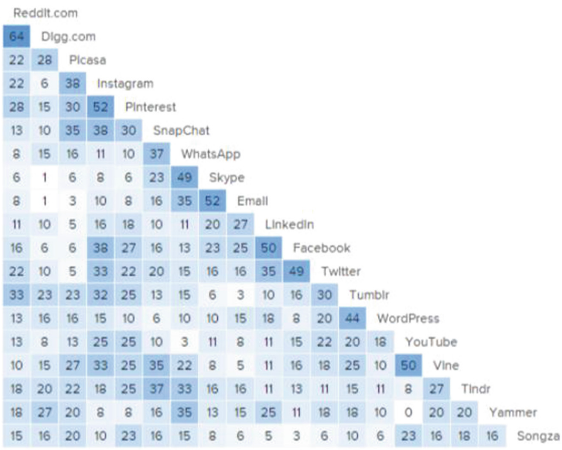

Fig. 1. Similarity matrix for 19 social media platforms (59 participants)

Decision Rule 1 Basic Synonymy: Category labels that researchers agreed were synonymous on their face were standardized.

Decision Rule 2 Temporal Character: Categories that suggest time, periodicity, or routine were grouped together.

Decision Rule 3 s Pass Limit: After first standardization pass, researchers could only combine 2 categories at a time.

Decision Rule 4 Qualifying Language: Qualifying terms or phrases in category labels were decisive in determining synonymy. See Rule 1: Basic Synonymy.

Decision Rule 5 Noise Categories: Groups that were unclassifiable (researchers termed these as 'noise categories'), groups with no conceptual link among services in the category that the researchers could identify with confidence or consensus. Examples include category labels like 'Lookout!,' 'Meh,' etc., group labels where the group label terms themselves provide too little guidance to make a clear determination.

Decision Rule 6 Standardization Naming: Standardized categories were named using the term most commonly used among the category labels of the participants. Different terms were grouped under common descriptors or terms when the common term or descriptor represented a concept or activity shared by the terms (e.g. to curate content requires the browsing of content, hence a label that suggested or used the term 'curate' was standardized to 'Browsing').

Using Decision Rules 1–6 above the researchers reduced the participant categories to 44 standardized categories. The researchers ceased standardization when their consensus formation reached its limit; when they could reduce no further. Table 1 shows the standardized category labels.

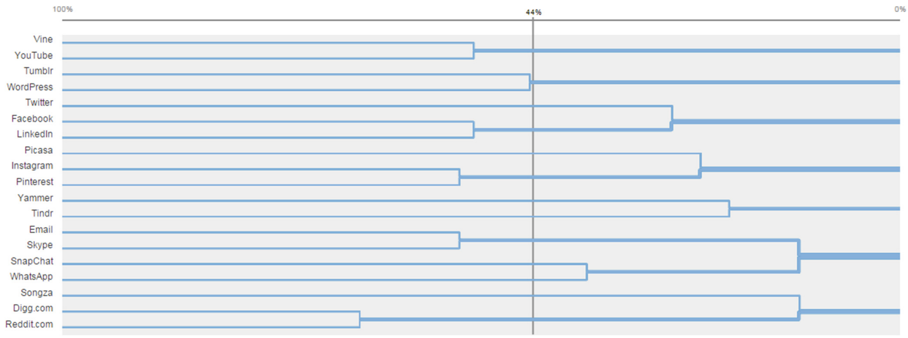

Fig. 2. Dendogram indicating pair relationships based on % agreement by participants

Table 1. Standardized categories identified by researchers

Aggregator	Content	Frequency	Network	Sharing
Blogging	Core	Fun	News	Social
Broadcasting	Dating	Hosting	Noise	Social ranking
Browsing	Don't use	Images	Occasional	Time killers
Business	Downtime	Information	old	Tools: images editing
Chat:text	Email	misc	Personal	Video
Communications	Entertainment	Multimedia	Photo	Visual
Communities	Favourites	Music	Private	watch
connecting	Forums	Necessary	Professional	

Using the strength of the association between paired cards, OptimalSort can execute a hierarchical cluster analysis to generate dendograms showing these relationships. The Actual Agreement Method generates a dendogram that shows the % of participants in agreement with actual groupings. These groupings are quite easy to pick out in Fig. 2. Information architects typically use these types of charts to identify how participants group content in comparison to proposed or current designs.

The dendogram helps to show how the social media platforms cluster together even though participants used different strategies for developing their categories. Table 2 shows the % Agreement for the top 7 pairs. Two sub-pairings are also presented in Table 2 to show the level at which a subsequent pairing occurs.

3 Discussion

Our study assumes a systems ecology of possibilities in the form of social platforms, situated in a common medium, and equally available to all the users who participated in our study. We maintain that as social media platforms consolidate or converge, the technical affordances of the platforms become less useful for explaining patterns of use. For example, Twitter.com can host lean, rich or richer media, as can Facebook.com, or nearly any other platform in our sample [31].

Based on the meta analysis described above, we determined that the categories 'social,' 'social ranking,' and 'communities' warranted further inquiry. Importantly, the term "social," as in society, and the term "community," overlap in the family of synonyms that cluster about them on paradigmatic grounds. Social and community connote the structure and the values of groups. The term 'social ranking,' however, introduces a distinction in the form of differentiation along strata, where some elements rise above others in priority, status, or perceived value. Community or social activity tend to indicate a group; systems of rank or ranking tend to indicate a tiered group.

The social media platforms that attached to the standardized categories, however, fail to support the affinity group-tiered group distinction. Figure 3 is organized by type and token. This means that tokens, are examples of platforms (like Digg.com or Pinterest.com) that attach to the larger category or type terms (like community or social ranking). Digg.com, for example, a social news site and tagging engine that filters content on grounds of participant response–a community-based ranking engine–appears in all three categories. Reddit.com, another social news site, also appears in all three categories. See Fig. 1, the Similarity Matrix, for how Digg.com and Reddit.com relate to other services. 64 % of the participants grouped Reddit.com and Digg.com together. Both are popular news and content aggregation sites that allow users of the service to post content that can be voted up or down by other users. This means a different form of analysis is needed to understand patterns between user categories, and platforms are too alike to support an affordances analysis alone.

As with natural language itself the types in the form of standardized categories and their tokens in the form of concrete social media platforms seem to relate to one another along lines of family resemblance [32]. This is not what one would consider to be a logical way of making sense of social media, is not a symbolic way of making sense of social media and does not conform to popular theories of social media use. To identify

Table 2. Relationship strengths indicating paired relationships

Pairing	% Agreement	Subpairing	% Agreement
Digg.com			
Reddit.com	65		
Instagram			
Pinterest	52	Picassa	24
Email			
Skype	52		
Facebook			
LinkedIn	51	Twitter	27
Vine			
YouTube	51		
Tumblr			
WordPress	45		
SnapChat			
WhatsApp	37		

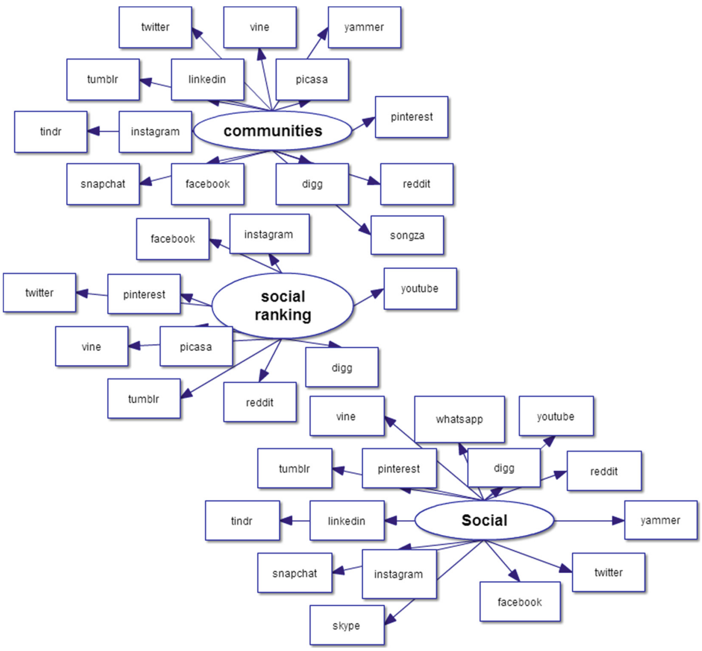

Fig. 3. Standardized categories 'social,' 'social ranking,' and 'communities' as logic trees. The child categories are the services the participants sorted into like groups at various levels of frequency.

by means of statistical inferencing across broad samples the denser clusters of semantic pattern–where terms or like terms appear in the company of other terms with higher frequencies–is the principle that guides that both corpus linguistics and the study of semantic graphs, therefore it is reasonable to use a network analysis to understand the social media platforms. When we treated the social media platforms as three semantic meta-networks, we were able to produce the following network diagram, Fig. 4.

The resulting merged meta-network yielded 17 unique nodes for a network density–or measure of actual as opposed to potential connections–of 46 %. Betweeness centrality—a network metric—registers the percentage of paths that pass through a node. Nodes with high betweenness centrality indicate mediating elements. Skype, and Songza, though they each appear in only one of the merged meta networks as seen in Fig. 3, register at the highest level of betweenness centrality in Fig. 4 at 0.091 and 0.047 respectively. Digg.com, by way of contrast, though it appears at a frequency of 3 in the merged meta-networks, falls below the top 10 in betweenness centrality. Importantly, this reveals user preferences that an affordances framework and standard survey instruments would probably fail to detect.

Skype and Songza are less generalized platforms of communication or content delivery; one specializes in social playlists and music delivery, the other in voice and video calls. They are easier to differentiate among platforms in a rich environment of platforms. Whereas other platforms blend and merge into a generalized field of services

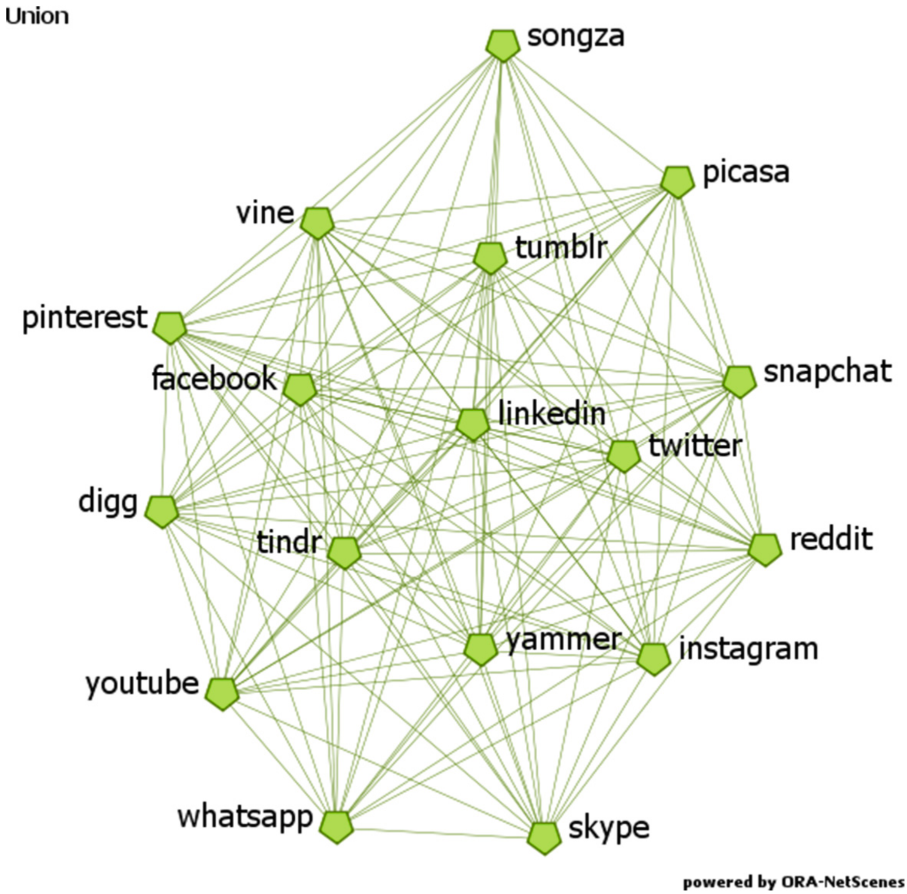

Fig. 4. Social media platforms that attach to the categories social, social ranking, and communities expressed as the union of three meta-networks (adapted from [33]).

where choice may be less clear, Skype and Songza assume a more specific character. This expresses itself in a semantic network as betweenness centrality. This finding would predict that similarity strength, or a platform's similarity or relations of similarity with other platforms defeats a sense of a clear choice among services. In other words, the only time affordances can predict user choice is when the platform in question is sufficiently different in features from every other platform. Otherwise, it may be social connections, trendiness or other contextual factors that are driving trends in use.

4 Conclusion

The ecology of social media platforms may be described by

(a) the services they offer,
(b) the technical affordances they support

(c) the opportunities they offer to develop, circulate, and curate content
(d) the opportunities they offer to discover or to develop contacts and relationships, and to connect with or to develop affinity groups

It is the primary assumption of this research that (a)–(d) underdetermine patterns of user selection among platforms or services within platforms because of the redundancy of services or opportunities among platforms, because of the tendency of users to use only the most immediate means to meet the most immediate need without respect to the richness of any platform's feature set, and because the experience of users with any objective process tends to develop independently of the process itself [31]. We hypothesized that users would sort the social media platforms that they use or that they know about based on criteria that include services, technical affordances, and so forth, what we referred to as "platform sorts" or "content sorts" But we also hypothesized other criteria consistent with categories of work, leisure, or social influence, sorts like liking, compliance-conformity, or reciprocity [31].

On its face our pilot study findings support our hypotheses. The Similarity Matrix derived from user responses is consistent with prior literature on the relative degree of use and familiarity of social media platforms, with Facebook.com, Twitter.com, and other familiar services, dominating user consciousness of what opportunities for social media activity exist. Where our methodology as evidenced by our findings may offer a unique contribution is at the level of user perception. User perception, we would argue, when conditioned by choices among rich feature sets, tends to blur platforms into a generalized field of activity that can be freely sorted any number of ways. The generalized platform such as Facebook.com, Twitter.com, or Wordpress.com, seems to follow a Walmart generalist strategy of non-differentiation by design, where Skype or Songza, by way of contrast, seem to follow a boutique strategy of differentiation by means of content or medium specialization.

If the generalized field hypothesis holds we would expect to find folds or concentrations that obtain between or among services as users would select among services or opportunities not based on platform but on combinations of services that may obtain across platforms, such as using Tumblr to park images from Instragram.com or Imagur.com, of Facebook.com to circulate memes from Tumblr or WordPress.

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