Using Affordances to Improve AI Support of Social Media Posting Decisions

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ABSTRACT

Intelligent systems are limited in their ability to match the fluid social needs of people. We use affordances—people's perceptions of the utilities of a target system—as a means of creating models that provide intelligent systems with a better understanding of how people make decisions. We study affordance-based models in the context of social network site (SNS) usage, a domain where people have complex social needs often poorly supported by technology. Using data collected via a scenario-based survey (N=674), we build two affordance-based models about people's multi-SNS posting behavior. Our results highlight the feasibility of using affordances to help intelligent systems support people's decision-making behavior: both of our models are ∼15% more accurate than a majority-class baseline, and they are ∼33% and ∼48% more accurate than a random baseline for this task. We contrast our approach with other ways of modeling posting behavior and discuss the implications of using affordances for modeling human behavior for intelligent systems.

CCS CONCEPTS

• **Human-centered computing → Social networking sites**; **Social media**; **Social content sharing**; **User models**.

KEYWORDS

Affordances, Social Media Ecosystems, Multi-site Posting

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1 INTRODUCTION

Artificial Intelligence (AI) systems are increasingly ubiquitous, with applications ranging from intelligent assistants in the workplace and smart home devices to Machine Learning (ML) models for complex decision-making settings such as medicine or criminal justice. However, AI-based systems perceive a domain using only the set of features designed specifically for their use. For example, an intelligent email assistant can use keywords in emails to propose meeting times, but cannot update the inbox's organization to match people's dynamic priorities. As such, AI's representation of a domain might not meet people's use of it. Indeed, Ackerman defines this mismatch of granularity between AI's rigid representation of a domain and the fluid social needs of people as a *socio-technical gap* [2].

One potential approach for bridging this socio-technical gap is to rely on people's model of a system's capabilities and iterate on system features accordingly. Prior work defines this people-centric view of a system's capabilities in terms of *affordances.* According to Gibson, "affordances are properties taken with reference to the observer" [13, p.135]—objects may have intended features that distinguish them from other objects, but what distinguishes people's use of different objects is their perception of the objects' features [13, p.126]. We hypothesize that this relationship between affordances and object usage translates to the online sphere.

We study the potential benefits of eliciting and using people's perceived affordances for predicting posting behavior in the social media ecosystem. We investigate social media posting behaviors because they are a rich example of fluid social needs—people constantly navigate nuanced media and audience considerations across multiple social network sites (SNSs). Thus, our primary research question is: ***how well do affordances explain people's posting decisions in the social media ecosystem?*** Prior work suggests that SNS posting must be carefully considered given the audience repercussions that might ensue, and advocates for an affordance-based approach in studying SNS ecosystems [45]. If a system could capture the affordances that people perceive in their SNSs, it would be able to provide better support for decision-making.

We conduct a scenario-based survey with 674 active social media users recruited on Mechanical Turk. Our survey is designed to elicit people's posting decisions for various hypothetical communication scenarios, via two sets of questions: (1) the affordances that people *desire* for posting in a given hypothetical scenario, and (2) the affordances they *anticipate* in each SNS they use. Using this data, we test the explanatory power of affordances by building: (1) a simple *Matching Model* that suggests SNSs for posting based on closest match(es) of desired and anticipated affordances, and (2) an *SVM-Based Model* that learns posting behavior using ML classifiers.

Our results are a strong initial signal that affordances can explain people's SNS posting decisions. Our models make ∼33% and ∼48% more accurate posting decisions compared to a random baseline, respectively. Our SVM-Based Model is also ∼15% more accurate than a majority-class baseline defined based on the popularity of each

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SNS. We discuss our approach in the context of other potential modeling approaches (e.g., habitual or heuristics-based usage models), and end with implications for a practical application: intelligently supporting people's posting behavior in their SNS ecosystem.

2 RELATED WORK

2.1 Challenges of Multi-SNS Posting Decisions

As multi-SNS use becomes more prevalent, people have to manage audiences, media, and features across multiple platforms. Zhao et al. [45] interviewed 30 people who use multiple SNSs and identified two tensions: (1) the tension between separating communication on multiple SNSs or letting it permeate across SNSs based on audience and content norms, and (2) the tension between having a stable SNS ecosystem or adopting new SNSs because they provide new opportunities for fulfilling heterogeneous needs. Similar findings were noted in a longitudinal study of Microsoft employees' SNS use by Zhang et al. [44]. These tensions illustrate the gap between offline, analog social rules and the platforms that support them.

2.1.1 ***Audience Management.*** Audience management—at the heart of Zhao et al.'s [45] separation-permeation tension—has been studied extensively. When it comes to online audience, social media users suffer from context collapse: "the flattening out of multiple distinct audiences in one's [offline] social network, such that people from different contexts become part of a singular group of message recipients" [37]. Context collapse is problematic because it often leads to sharing the same content with people from different contexts that the poster would have liked to keep separate.

One strategy people use to avoid such situations is to post based on habits or heuristics. Heuristic processing reduces the cognitive effort required in carefully making decisions about which platform to post on. Under this processing, there is a level of "automaticity" in making decisions, such as "lack of intention, lack of awareness, involuntariness, noninterference with other ongoing mental processes" [3]. One common heuristic used for posting is to follow a lowest common denominator approach—only share content that is relevant for all audiences [16]. While this reduces the risk of sharing something with the wrong audience, people have to heavily censor their SNS use, which may limit their ability to be disclosive in an SNS [20, 38]. Another common heuristic that people apply is the availability heuristic: selecting options that are more easily retrieved [31, 36]. For the SNS ecosystem domain, this means selecting the SNSs for which they can easily recall prior posting instances. With this heuristic, it is likely that people will use fewer SNSs than they could if they systematically thought about their choices.

Another strategy people use to avoid context collapse is to separate people who belong to different contexts by using multiple SNSs, i.e., maintaining different personae for each SNS [23, 33, 44, 46]. While this prevents context collapse, it requires additional time and effort when posting something: people have to carefully think about their audience choices across multiple SNSs and whether they want to enforce the boundaries or let the content permeate across them. By building intelligent assistants that support decision-making in this setting, our hope is to help people with multi-SNS posting without spending additional time and effort or being biased by heuristics.

2.1.2 ***Ecosystem Management.*** In line with the other tension identified by Zhao et al. [45]—the stability-change tension—Zafarani and Liu [43] study why people join multiple SNSs. They find popularity of a site and peer pressure from social connections to be common reasons. However, as their SNS ecosystems get bigger, people get more selective and consider the utility they would obtain from joining a new SNS. Zhao et al. [45] hypothesize that this utility is dependent on how well the new platform bridges the socio-technical gap. The role of the socio-technical gap in people's multi-SNS use is challenged by LaRose and Eastin's [22] and LaRose's [21] findings that people's media use is dependent on habits, i.e., people do not carefully consider how platform features meet their social needs. Rather, they choose which SNSs to use based on the habitual use of certain SNSs over others. Modeling SNS behavior as we do here can explore whether people make choices based on careful consideration or habits. Additionally, if people's use is found to be habitual or heuristics-based, these models can provide recommendations based on needs people might not have considered.

2.2 Ecosystem-Level Usage Models

One popular domain that has built models for explaining multi-site use is information seeking. Morris et al. [25] conducted a survey of Microsoft employees to model their use of Facebook and Twitter for status message question asking (SMQA). They provide a breakdown of the question types and topics people asked of their social networks. Oeldorf-Hirsch et al. [28] further used Morris et al.'s model of question types and topics as a means of generating hypothetical information-seeking scenarios for their study. They used these scenarios to model not only multi-SNS SMQA behavior, but general information-seeking behavior across SNSs and search engines. This model let them answer the question of "which needs go where," and thus inform automated routing tools in that domain. For our study, the methodology is similar to Oeldorf-Hirsch et al. [28]: we employ a hypothetical scenarios-based survey to build models that explains multi-SNS usage for posting content.

2.3 Using Affordances to Inform Models

Prior work in ubiquitous computing has relied on physical affordances of objects to model people's use of new sensing devices and iterate on their design (e.g., in [18, 30, 34]). However, with our online ecosystem-level setting, we needed a platform-agnostic way to characterize the ecosystem. Previous work has advocated viewing individual platforms as "collections of features" [32] because people make decisions about sharing on a platform by evaluating these features [19]. People have different perceptions of platform features, and these perceptions might map their usage of the platform [45].

The above literature compelled us to look at affordances—the perceived utility obtained from using a feature—as the factor that could explain multi-SNS usage. Prior work supports this approach: work by boyd [5], Ellison and Vitak [11], Treem and Leonardi [35], Zhao et al. [45], and others (e.g., [7, 32]) calls for a perspective grounded in affordances when characterizing SNSs. Thus, we decided to test affordances for our platform-agnostic multi-SNS usage model.

Affordances are relative to each user, and they are anticipated by each user based on the features of a site that matter most to them. In this way, affordances are tied to the unique ways in which

<table>
<tr><th>Affordance Category</th><th>Description</th><th colspan="2">Values</th></tr>
<tr><td>Visibility</td><td>"means, methods, and opportunities for presentation"</td><td colspan="2">text, image, video, link, or other media</td></tr>
<tr><td>Persistence</td><td>whether the content persists or disappears (i.e., ephemerality)</td><td colspan="2">delete automatically after sometime, allow people to revisit and delete, content available permanently</td></tr>
<tr><td>Editability</td><td>craft or edit content</td><td colspan="2">N/A (we did not test this because it is allowed consistently by all SNSs we study)</td></tr>
<tr><td rowspan="5">Association</td><td rowspan="5">established relationships</td><td colspan="2">Multiple Constructs</td></tr>
<tr><td>Construct</td><td>Values</td></tr>
<tr><td>Audience Type</td><td>friends, family, professional connections, people you meet online, people you don't know at all</td></tr>
<tr><td>Audience Size</td><td>small, medium, large</td></tr>
<tr><td>Audience Boundary</td><td>sharing with specific individuals, a custom list of people, everyone in your social network, public</td></tr>
</table>

Table 1: Concrete social media features corresponding to each affordance category from Treem and Leonardi [35].

people perceive and use different site features [13]. The affordances literature (e.g., [5, 32, 35]) provides useful descriptions of SNS affordances. To concretize this affordance perspective, we follow Treem and Leonardi's categorization of social media affordances [35]. They follow Gibson's definition of affordances [13] and provide example features corresponding to their four affordance categories—this simplifies the process of concretely operationalizing an initial set of features for each category. These affordance categories are:

- **Visibility** refers to the "means, methods, and opportunities for presentation" allowed by SNSs, i.e., how information is presented on a SNS.
- **Persistence** conveys whether the information presented on these sites persists or disappears, i.e., the ephemerality of content on a SNS.
- **Editability** is the ability for a user to craft or edit their content before and after making it available on a SNS.
- **Association** refers to the established relationships between individuals or individuals and data.

3 METHODS

3.1 Operationalizing Affordances

Affordances explain people's perceptions of features at a platform-agnostic level, but simply asking people about the affordances they perceive when using SNSs is too open-ended. Instead, we infer the importance of different affordances by asking people about the features of the platform that implement each affordance. To obtain a set of features for each category, we used the examples provided by Treem and Leonardi [35] for each affordance category and coded them as being platform-specific or platform-agnostic (i.e., present in multiple SNSs). For example, for visibility affordance, people can make their content visible to others via Twitter's 280-character text (platform-specific) or simply using text (platform-agnostic). Since our goal is to model ecosystem-level posting, we rely on platform-agnostic features. Table 1 presents our affordance categories and the corresponding features. Using these categories, we designed a survey to elicit information about people's affordance considerations when posting content (*desired affordances*) and the affordances they perceive in the SNSs they use (*anticipated affordances*).

3.2 Hypothetical Scenarios for Posting Content

We generated hypothetical scenarios for situations in which people post content on social media to elicit information about people's posting behavior without scraping or collecting data from all of their SNS profiles. This is a common technique employed in the SNS literature (e.g., [25, 28]). These scenarios were generated based on the following dimensions, also grounded in prior work:

- **Content Type**: We employed Naaman et al.'s [26] terminology of content types shared online: *personal*, which is about the person doing the expressing or things related to them; and *impersonal*, which is informational in nature.
- **Communication Type**: Prior work is split between studying posting for the purposes of *sharing information* versus *seeking information*. For example, [27, 39] focused on understanding sharing on individual SNSs—in which people share information they have—and [14, 29] did so across a subset of SNSs. On the other hand, [12, 17, 25] described seeking information, in which people post content with the goal of requesting information (e.g., a restaurant recommendation).
- **Topic**: Prior work describes a range of topics that have been observed in social media posts. We iterated over a list of topics found by this literature (for example, in [25, 29, 39, 42]), and grouped similar topics to end up with a list of 12 commonly studied topics. This includes Big Life Events, Crisis Information, Politics, and more (Table 2).

We use these three dimensions (Table 2) to generate 48 ($2\times2\times12$) unique hypothetical scenarios used in our survey. E.g., the scenario generated for {Content Type = Personal, Communication Behavior = Sharing, Topic = Health and Medicine} was "You achieved your most recent health goal and want to share your accomplishment."[1]

[1] All hypothetical scenarios are included in the supplementary material.

		Content Type		x 12 Topics
		Personal	Impersonal	Arts/Culture/Literature, Quotes, Crisis, Politics, Holiday and Travel, Health and Medicine, Food and Cooking, Technology and Science, Nature and Weather, Style and Fashion, Big Life Events, Professional Information
Communication Type	Sharing	1	2	
	Seeking	3	4	

Table 2: Dimensions for generating hypothetical scenarios.

3.3 Survey

We conducted a two-part between-subjects survey, implemented in Qualtrics. The survey began by asking participants basic demographic information and which SNSs they had used at least once in the last 3 months (Pew Research Center's metric for active use of social media [9]). We included 10 SNSs in the survey—Facebook, Twitter, Instagram, Reddit, Pinterest, Google+, Snapchat, LinkedIn, Tumblr and Flickr—selected by taking a union of SNSs studied by Pew Research Center [9, 10] and those on Alexa's top 500 most visited sites list [1]. Only participants who used at least three of these ten platforms were forwarded to the remainder of the survey.

3.3.1 ***Survey – Part One – Desired Affordances.*** The first part of the survey sought to identify people's desired affordances for posting content. We presented each participant with one of our 48 hypothetical scenarios and asked two sets of questions in a randomized order. The first set of questions asked about the features (corresponding to different affordance categories from Table 1) that they would use to meet the hypothetical communication need in the scenario. People could also indicate that "I would not share anything for this scenario" (Figure 1). This option was provided to ensure that our results reflect valid communication needs. The second set of questions asked participants to select their best choice of SNS to post something for the given scenario and any SNSs they would *not* use for this scenario. This second set of questions represented our ground truth. We also asked open-ended questions about people's choices to better understand their selections.

Ideally, each participant would answer questions for all 48 communication needs, to give us a comprehensive dataset. However, during informal pilot testing, we found that people spent 7–10 minutes answering questions for one scenario, thus it would take 5–6 hours for all 48. To reduce this burden, we chose a between-subjects design and presented everyone with only one of the 48 scenarios.

In generating the hypothetical scenarios, we were concerned about the amount of specificity to include per scenario because specificity vs. generality has a long history of altering results in the human-computer interaction literature (e.g., [4]). To alleviate this concern, we generated an equal number of general and specific scenarios: we randomly picked 24 out of our 48 scenario categories to be "general" and 24 to be "specific," and generated scenarios based on these pre-coded guidelines for specificity levels. After the survey was complete, we modeled the specificity versus generality using logistic regressions to test its influence on the selection of any of our affordance categories when posting content, but found no evidence of impact (all p-values were between 0.5 and 0.8).

3.3.2 ***Survey – Part Two – Anticipated Affordances.*** For part two, our goal was to gather data about the anticipated affordances of each SNS that the participants reported actively using. For each

Scenario: **You read the latest book by your favorite author and want to share your opinion of it.** Please answer the following questions keeping this scenario in mind.

1. **Which of the following media would you use to post something to your social network(s) for this scenario?**
   - ❏ Text
   - ❏ Image
   - ❏ Video
   - ❏ Link
   - ❏ Other (Please Specify) _____
   - ❏ I would not post anything for this scenario
2. **What would be the ideal audience size with whom you would share the post?**
   - ○ Small
   - ○ Medium
   - ○ Large
   - ○ I would not post anything for this scenario
3. **How are you connected with the people with whom you would share the post?**
   - ❏ Friends that you knew in-person first
   - ❏ Family
   - ❏ Professional Connections
   - ❏ People you met online
   - ❏ People you don't know at all
   - ❏ Other (Please Specify) ____
   - ❏ I would not post anything for this scenario
4. **How would you select the people with whom you would share the post? Would you select:**
   - ❏ Specific individuals relevant for this scenario
   - ❏ A predefined, custom list of people from your social network
   - ❏ Everyone in your social network
   - ❏ Public
   - ❏ Other (Please Specify) _____
   - ❏ I would not post anything for this scenario
5. **Would you want the post to automatically disappear from your page after a certain amount of time?**
   - ○ Yes
   - ○ No, but this is something I might delete on my own after some time
   - ○ No, I would be okay with this being available permanently
   - ○ Other (Please Specify) ____
   - ○ I would not post anything for this scenario

Figure 1: Survey Part One: Questions about desired affordances. Checkboxes indicate questions for which people can select multiple answers; bullets indicate single choice. Part Two uses the same questions, worded differently to elicit information about each SNS's anticipated affordances instead.

platform that they said they used, we questioned participants about frequency-of-use and the affordances they anticipated in said platform. The questions were similar to part one (Figure 1), modified to ask about specific SNS usage (e.g., "I share the following media on Facebook:" instead of the original "Which of the following media would you use to post something to your social network(s) for this scenario?"). The language was also modified depending on the SNSs' terminology (e.g., calling connections on the SNS "friends" or "followers"). Whenever applicable, we gave our participants the option to say "I do not post/share on [`platform name`]" to ensure that they did not have to answer questions about expressing communication needs on a platform when they did not use it for that purpose (e.g., when they were only consumers of content or "lurkers").

3.4 Participants and Data

We recruited participants through Amazon Mechanical Turk, requiring participants to be located in the U.S. and have a HIT acceptance rate of at least 97%, and paid them \$0.80 for ~5 minutes of their time. We received 807 responses overall; 133 of these failed one or more of these validation checks: (i) did not actively use at least 3 SNSs, (ii) did not provide data about any SNS usage by choosing the option "I do not post/share on [`platform name`]" for all questions, or (iii) did not answer the attention check question consistently (same question asked twice, with different ordering). After removing these responses, 674 participants remained in our dataset. These participants were distributed evenly across our 48 hypothetical scenarios (mean=14, s.d.=2). Our participant demographics matched Mechanical Turk's population demographics except for a larger percentage of people in their 20s in our sample (36%) than Mechanical Turk's overall demographics (20%) [8]. This was not surprising since that age range represents most frequent social media users.

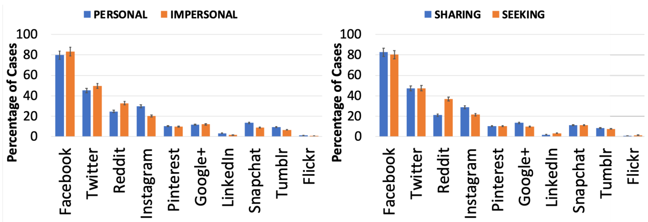

Figure 2: Percentage of times each SNS is used for Left: different content types, Right: different communication types.

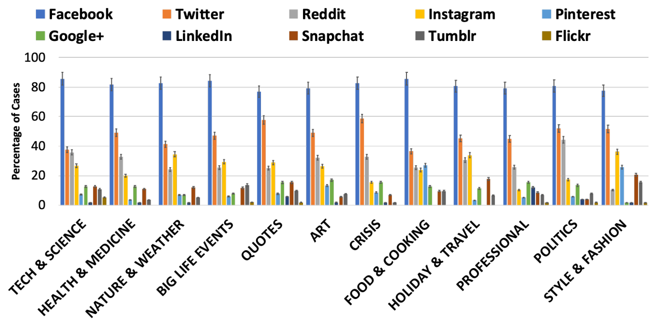

Figure 3: Percentage of times each SNS is used, by topic.

3.5 Overview of Dataset

Participants in our survey used an average of 4.38 SNSs, and posted about the same scenario to 53.54% (2.34 SNSs) of them. To further explore patterns in our participants' posting decisions, we plotted 3 histograms that present the percentage of cases of SNS use for each of our conditions: two content types (Figure 2-Left), two communication types (Figure 2-Right), and 12 topics (Figure 3).

Facebook is the most popular SNS for intended posting across all categories. This is not surprising given Facebook's popularity, based on data from PEW Research Center [15]. According to the PEW report, Facebook, Instagram, Pinterest, LinkedIn, and Twitter are the most popular SNSs, in that order. In our dataset, we find the order to be slightly different in two ways: Twitter is the most popular SNS after Facebook, and LinkedIn's popularity is far lower. These differences in our dataset and PEW's social media update could be an artifact of survey methodology differences—while we use hypothetical scenarios and self-reported data, PEW Research Center uses interviews and asks people to list the SNSs they use, but does not ask for the context in which people post content. We believe that our dataset thus captures a wider range of posting situations, and this might be why some of these numbers are different.

Another interesting trend in Figures 2–3 is that the error bars are bigger for the more popular networks (e.g., Facebook, Twitter, Reddit, Instagram) as compared to the less popularly used ones (e.g., Snapchat, LinkedIn, Google+, Tumblr). This would imply that people use the less popular SNSs for specific posting needs, whereas they share a wider range of content on the more popular SNSs, allowing for more variance. Our dataset thus incorporates not only a variety of scenarios, but also varied SNS usage rationales. Note that these trends and demographics are representative of the time when we collected our data (in 2016), and may have changed over time.

4 MODELS

We construct two competing models: the first performs binary matching between the desired affordances for a post and the anticipated affordances of each SNS; the second uses a Support Vector Machine (SVM) classifier with a feature set comprised of both the desired and anticipated affordances. The first approach results in an intuitive, non-ML model that lets us test the explanatory power of affordances given uniform weights for each affordance. The second approach tests the explanatory power of desired and anticipated affordances by using ML to help uncover the importance of specific features (affordances) over others.

4.1 The Matching Model

The Matching Model aligns the anticipated affordances for each SNS that a person uses with the desired affordances for the content they wish to post, and then scores each SNS based on the number of affordances matched. The model then makes two predictions: (1) the best matching (highest scoring) SNS as the most likely for posting content, and (2) the top 53.54% matching SNSs as the set of SNSs suggested for posting. We use the 53.54% top matches because that is the average percentage of SNSs that users in our dataset posted to. These predictions are compared to our baselines using the evaluation metrics described in the next section.

4.2 SVM-Based Model

An assumption underlying the Matching Model is that all affordances matter equally to everyone; we do not weight individuals' affordance options differently. However, in reality, people might be more concerned about audience size when posting a controversial political opinion or concerned about the type of media when sharing a major life event. To capture differences such as these, we use ML methods to construct a model that learns the relative importance of individual desired and anticipated affordances.

We implement this as a set of 10 Support Vector Machine (SVM) classifiers—one per SNS—with data from all users per SNS. We tested several other models for this classification task (e.g., Logistic Regression, Decision Trees, Random Forest); SVMs performed marginally better than other options. Note that the difference in performance was not significant (all $p > 0.1$). We do not rely on more complex architectures (e.g., neural networks) in this initial exploration of affordance-based modeling because we need intelligible models to observe the underlying affordance signal.

There are N feature vectors generated per participant, where N is the number of SNSs the participant uses. Each feature vector comprises of a participant's desired affordances and the anticipated affordances of one out of N SNSs they use. Each SVM classifier represents an SNS class and outputs a binary Yes/No answer for whether the participant should post to the SNS being considered. The performance results are calculated after applying a 5-fold stratified cross-validation for each SVM. We aggregate the per-SNS outputs for each participant to find their final set of SNSs selected for posting by the model. This has the advantage of not requiring a general selection of 53.54% SNSs for everyone—the model is capable of selecting the right number of SNSs for posting based on each individual's ecosystem-level data.

5 EVALUATION METRICS

We test our models against ground truth data obtained from participants through our survey. Survey questions about people's best choice of SNS for posting in a scenario and the SNSs they would not use in that setting provide this ground truth. The data is compared using the metrics described below. We also measure significance using two-tailed, paired t-tests.

5.1 Precision @ 1

To find an upper bound on the precision that our models can achieve using affordance information—subject to non-zero recall—we calculate the percentage of cases (sets of predictions) for which at least one SNS that the model selects for posting is also one of the SNSs selected by the participant. This is a test of our models' best-case performance in terms of precision because we choose the smallest non-trivial set of selections that our model can contribute with the highest confidence (the empty set would vacuously give 100% precision, but does not contribute a useful model).

5.2 Precision and Recall

Our primary measures of model performance are precision and recall over SNS selections. Precision measures the number of instances selected by the model that are also relevant according to the participant. Recall measures how many relevant instances chosen by the participant are also selected by the model. We also calculate F1 score for each participant, which is a joint measure of both precision and recall—the harmonic mean of precision and recall values. F1 scores let us evaluate our models using one number that jointly represents both precision and recall. We compute each metric per participant and report the average across participants.

5.3 Baselines

We evaluate our models by comparing their performance in terms of the above metrics the two baselines described below. As noted in the Models section, we do not present results from other ML models as baselines since the performance is similar across them.

5.3.1 ***Random Baseline.*** Evaluating the results of models against randomly generated results is a popular evaluation methodology employed in the field of machine learning. It serves as a proxy for how a system with no intuition about SNSs would make posting decisions. We calculate two types of values for this baseline: (1) randomly selecting one SNS from each participant's ecosystem for posting, for comparing the precision@1 value; and (2) randomly selecting 53.54% of SNSs in each participant's ecosystem for posting, for comparing the precision, recall, and F1 score values. As noted above, we pick 53.54% of SNSs in each participant's ecosystem since that is the average percentage of SNSs people use for posting among all SNSs present in their ecosystems. For our random baseline, precision@1 = 22.83%, calculated by randomly selecting one out of the average 4.38 SNSs in our participants' ecosystems. Precision = 52.84%, recall = 28.36%, and F1 score = 35.45% (Table 3).

5.3.2 ***Popularity Baseline.*** Prior work on SNSs has highlighted the popularity of these SNSs as a common heuristic used by people in deciding where to post content. We reflect this in a majority-class baseline, where majority is defined based on global ranking of popularity of SNSs. We calculate this global ranking of SNSs depending on how many people use each SNS in our study (order: Facebook, Twitter, Reddit, Instagram, Pinterest, Google+, LinkedIn, Snapchat, Tumblr, Flickr). We calculate two values using this order: (1) always selecting the one most globally popular SNS also present in the individual's ecosystem, for comparing the precision@1 value; and (2) selecting 53.54% of SNSs in each participant's ecosystem in the order of the most globally popular SNSs, for comparing with precision, recall, and F1 score values. For example, if a participant uses Instagram, Snapchat, Twitter, and Pinterest, the (2) part of this baseline would predict Twitter and Instagram for this participant. Our popularity baseline has: precision@1 = 84.57%, precision = 65.69%, recall = 70.58%, and F1 score = 68.05%.

6 RESULTS

6.1 The Matching Model

6.1.1 ***Precision @ 1 Performance.*** The Matching Model has a best-case precision of 83.53%—matching participants' desired affordances to affordances anticipated in each of their SNSs, then picking the highest confidence SNS, outputs an SNS that was also selected by the participant 83.53% of the time (Table 3). This outperforms the random baseline by 60.70% (improving from 22.83% to 83.53%) and is on par with the popularity baseline (83.53% compared to 84.57%). The similarity in values for Matching Model and popularity baseline suggests that the highest scoring SNS from the Matching Model matches the most popularly used SNS for an individual.

6.1.2 ***Precision/Recall Performance.*** We calculate the resulting precision, recall, and F1 score for each participant and report averages across all participants. The Matching Model has an average precision of 70% and an average recall of 66.24%, giving an average F1 score of 68.07% (s.d. precision=15, recall=15 and F1 score=13). This means that from the set of SNSs selected by the Matching Model, 70% are also selected by participants for posting content, on average. Furthermore, the set selected by the model includes 66.24% of all relevant SNSs the participants would have wanted, on average. Compared to our random baseline, the Matching Model performs better overall: increasing 17.16% in terms of precision, 37.88% in terms of recall, and 32.62% in terms of F1 score.

While the Matching Model significantly outperforms our random baseline (for all, $p << 0.001$), its performance is not better than the popularity baseline. The popularity baseline has a significantly better recall than the Matching Model ($p << 0.001$), but there is no significant difference in the precision and the overall F1 score between the two. The high recall value of the popularity baseline is an artifact of selecting the most popular SNSs for posting from our dataset. It is not unexpected that the popularity baseline outperforms a heuristic approach based on simple, unweighted matching between desired and anticipated affordances in terms of recall.

6.1.3 ***Implications.*** Our results for the Matching Model provide an initial signal for the benefits of using affordances to understand and model SNS ecosystem posting behavior. Out of all SNSs selected for posting using this model, 70% were also selected by the participant, on average. The goal of this matching methodology was to serve as a proof of concept—the improvement from random baseline

	Random Baseline	Popularity Baseline	Matching Model	SVM-Based Model
Precision @ 1	22.83	84.57	83.53	**99.85**
Average Precision	52.84 ± 17	65.69 ± 14	70.00 ± 15	**80.23 ± 13**
Average Recall	28.36 ± 20	70.58 ± 13	66.24 ± 15	**85.10 ± 12**
Average F1 Score	35.45 ± 15	68.05 ± 12	68.07 ± 13	**82.59 ± 9**

Table 3: Comparison of multi-SNS usage models based on our evaluation metrics. The bolded numbers indicate the top-performing model along each metric used. Here, the SVM-Based Model always shows the best performance.

and the overall comparable performance to the popularity baseline, even with this basic approach, is a compelling indicator that affordances can provide accurate explanations for some of people's posting behaviors in their SNS ecosystems. The Matching Model also acts as a comparison point for predicting SNSs for posting using only a simple, unweighted set of affordance-based features.

6.2 SVM-Based Model

6.2.1 ***Precision @ 1 Performance.*** To compare precision@1 performance, we obtain the best single-choice SNS given by the SVM-Based Model. We do so by calculating the distance of each SNS from the classification boundary (decision surface)—the larger the distance, the more confident we can be in the prediction—and then pick the highest-confidence answer (or answers, in the event of a tie). We find that our single-choice SNS(s) are correct for 99.85% of participants, i.e., for 99.85% of participants we are able to correctly identify at least one of the SNSs that they would post to. The SVM-Based Model outperforms the random baseline in terms of precision@1 by 77.02%, and the popularity baseline by 15.28%.

6.2.2 ***Precision/Recall Performance.*** For each user, we aggregate the results of our 10 per-SNS SVM classifiers, each of which predict either "Yes" or "No" for posting to the corresponding SNS. The result is a set of Yes/No decisions that we can compare to the ground truth from our survey, same as our evaluations thus far. Averaging the values across users, we find that an average of 80.23% of all predicted posting decisions are correct (s.d. precision=13). The benefit of training the SVM-Based Model is that it balances precision and recall: the SVM-Based Model correctly selects (recalls) an average of 85.10% of all SNSs selected by each participant (versus 66.24% recall for the Matching Model), an 18.86% improvement (s.d. recall=12). Thus, the SVM-Based Model has a F1 score value of 82.59% (s.d. F1 score=9). Compared to the random baseline, the SVM-Based Model has 27.39% higher precision, 56.74% higher recall, and 47.14% higher F1 score. The SVM-Based Model also outperforms the popularity baseline by 14.54% for precision, 14.52% for recall, and 14.54% for F1 score (all differences significant, $p << 0.001$).

6.2.3 ***Implications.*** With an SVM-Based Model grounded in affordances, we are not only able to more precisely select the set of SNSs used for posting (80.23% precision, on average), but are also able to select an average of 85.10% of the set of SNSs considered ideal for posting by the participant. Given the improvement in the performance of this model when compared to all our baselines, we observe that not only do affordances contain useful "signal" for explaining user posting behavior, but also the ability to outperform models with uniform affordance weights like the Matching Model (F1, p « 0.001). The viability of this approach has important implications for automation attempts in the domain of social media ecosystems: we now have concrete evidence that affordances can predict a significant number (~83% F1 score) of posting decisions made by people. By creating these initial models, we introduce opportunities for intelligent systems grounded in affordances to predict multi-SNS usage and, in doing so, present new baselines for future methods and systems in this space.

6.3 Understanding Where the Signal Lies

While our SVM-Based Model is effective, it remains somewhat of a "black box". To better understand which of our affordance-derived features were contributing the most to the overall performance of our model, we examined the weights learned on each of the features by the SVM classifier. Since we trained 10 classifiers for our testing (one per SNS), we aggregated the results by normalizing the coefficients and then averaging the weights on each affordance per SNS. Figure 4 shows a plot of each affordance that we operationalized, both as desired and anticipated affordances. For each affordance category, we averaged the absolute value of each constituent feature (since the polarity of the weight does not matter for prediction strength). While "a_permanence" affordance was most predictive, most affordances were weighted approximately the same, showing that each contributes similarly. Critically, training a single-affordance SVM classifier was not as effective as using all of the affordances together. To demonstrate this, we implemented versions of our SVM-Based Model that used only one affordance category. There was a significant improvement (all $p << 0.001$) when using all features over using each of them individually.

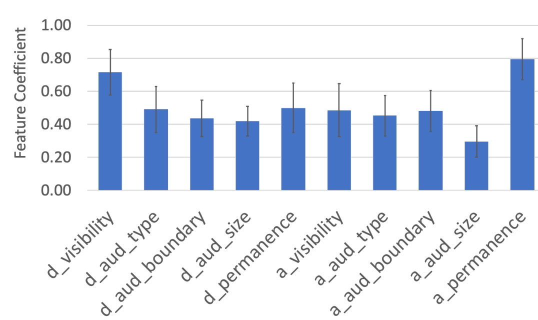

Figure 4: Average weights learned by the SVM classifiers for each affordance category. Desired affordances are prefixed with "d_" and anticipated affordances with "a_".

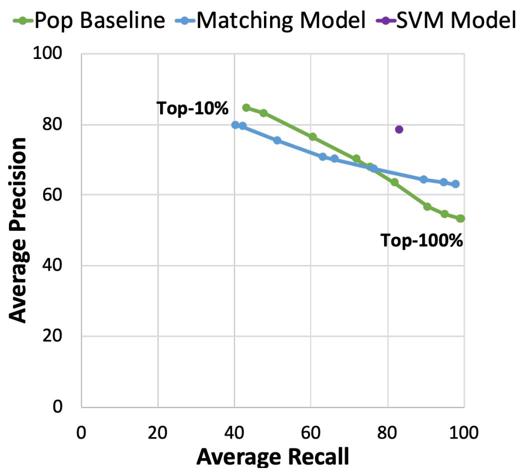

Figure 5: The trade-off curve (precision versus recall) for our popularity baseline and Matching Model as the inclusion threshold (percentage) for the number of SNSs predicted for a user increases. Each point from left to right indicates a 10% increase in the number of SNSs predicted per user. As expected, as more SNSs are included, recall increases and precision decreases. Our SVM-Based Model exceeds this trade-off frontier by being simultaneously higher precision and recall than comparable points in our two comparison cases.

6.4 Exploring Trade-offs in Threshold Selection

In the sections above, we evaluated our models against random and popularity-based baselines that selected 53.54% SNSs of people's actively-used SNSs. Our Matching Model also selected 53.54% of SNSs for each individual. Recall that we used this threshold because it is the average number of SNSs people used for posting. But this begs the question: what impact does the selection of an inclusion percentage have on the performance of our baseline (and thus on the improvement we observed in our methods)? Did our data-driven selection of 53.54% result in the strongest baseline possible given the methods we selected, and how much does it matter?

Figure 5 shows the trade-off curve (precision versus recall) that results from varying the inclusion threshold (percentage) for our n-best methods: the popularity baseline and Matching Model. From left to right, each point represents a 10% increase in the inclusion threshold, from 10% up to 100% of SNSs for each user. Recall that our SVM-Based Model automatically picks the number of SNSs to suggest posting to without relying on this threshold value, and thus it appears as a single point. In terms of F1 score, the 50% threshold was significantly better than most other points, except that it was not distinguishable from 40% or 60% (which are also, themselves, better than other thresholds in terms of F1). This implies that our threshold is centered in the correct range to maximize performance.

Further, Figure 5 shows that our SVM-Based Model outperforms both the popularity baseline and Matching Model's top-N SNS selections by pushing past the frontier of either curve (that is, being simultaneously farther up and to the right). This serves as evidence that our affordance-based models can predict people's posting decisions more accurately than other approaches, regardless of their exact tuning for the number of SNSs being selected.

7 QUALITATIVE EXPLANATIONS OF POSTING DECISIONS

We use qualitative data collected via open-ended responses in our survey to learn how people explain their posting decisions. Analyzing this data not only corroborates the use of affordances as people's rationale, but also helps us identify other important considerations people have. We conducted an inductive thematic analysis [6] of this qualitative data and generated various themes via affinity diagramming for the factors people consider. Below, we discuss these themes and present some representative quotes for each.

7.1 Audience Size

Prior work has shown that when people post something, they often have a sense of the ideal audience size they want to reach [24]. We see this theme in our participants' responses as well. For example, P315 shared their post about their state changing the minimum wage on Facebook because *"People like to share and like things on Facebook which would give my post a larger overall viewing audience."* When posting something to seek information in a scenario, participants try to access a large and diverse audience and rely on SNSs in their ecosystem that provide these audience characteristics for the particular seeking need. For example, P303 used Twitter to reach a large audience size to confirm a rumor about their favorite movie actor because *"I have lots of followers on Twitter that are movie buffs that could easily confirm or deny this rumor."* P219 selected Reddit when seeking advice about how to make a good presentation because they expect to reach a large, diverse audience there:

> *"On Reddit I could get decent advice from a good amount of people that would be from all different backgrounds, professions, etc. and that would be more useful to me than anything from my Facebook friends."* (P219)

7.2 Audience Composition

Managing the composition of their audience is another common rationale behind people's SNS selections. People choose to share different aspects of their lives with different types of audiences, ranging from family and close friends to strangers on a SNS [24, 45]. Most of our participants choose Facebook as the best SNS when posting personal life events or news because "*it is the most widely used social network among my family and friends*" (P228). Wanting a more professional audience for a scenario where they were looking for some guidelines on giving a good presentation, P296 chose LinkedIn for posting because:

> *"It is a professional network, so the audience reading the post would be very well versed in what makes a good and bad presentation."* (P296)

Audience composition not only includes different relationship types between the poster and their audience (e.g., friends, family, strangers), but also includes cases where people want to choose subsets of an audience based on a criterion. For example, P403 chose to share their post about their state changing the minimum wage on Facebook because of its "who should see this" posting feature:

> *"I want to be able to tell this to people I know who live in my state, and Facebook is the easiest way to do that thanks to settings on who can see certain things."* (P403)

7.3 Content Media

When making posting decisions, people consider how they want to share their post (e.g., as text, image, or other media) [45]. These media options often simplify people's decisions in selecting SNSs for posting. For example, if they want to post a link but the SNS does not import links, they can easily eliminate that SNS as an option for that post. P401 used this process of elimination to choose Facebook to share a review of the latest book by their favorite author:

> *"If I was sharing my opinion about a book (I know from extensive experience), it would be a relatively large chunk of verbiage, and Facebook is the best suited for that versus Twitter (or, really, any others)."* (P401)

This choice of media is unique, depending on the desired media for how a participant envisions their post. For the same scenario as P401 above, P302 mentioned images as their preferred medium, and used Instagram instead *"because it is the most visual and I can showcase the book in the most positive way through Instagram."*

7.4 Summary

These themes identified from our participants' open-ended responses corroborate our findings that rely on affordances for modeling multi-SNS posting decisions. The audience-related themes presented here are analogous to the audience-related affordance categories in our survey, and the content media theme is analogous to the visibility affordance we test (see Table 1).

8 DISCUSSION

Affordances—when appropriately operationalized—contain useful signals for automated techniques that could help people navigate their SNS ecosystems. This enabling technology is motivated by prior observations by researchers that a growing number of people are using multiple social media sites, but doing so can create difficulties in negotiating the relatively static features of sites that afford different interactions and the fluid needs of people for meeting their social goals [2, 45]. To conduct an initial test of the concept of intelligent systems in this complex social media ecosystem, we use affordances to inform platform-agnostic models for predicting multi-SNS posting behavior. We find that affordance-based models have high F1 scores—68.07% for the Matching Model and 82.59% for the SVM-Based Model (compared to 35.45% F1 score of the random baseline and 68.05% F1 score of the popularity baseline). The improvement in these numbers when compared to the random baseline and to a plausible, data-driven, majority-class model (the popularity baseline) provides support for the feasibility of building multi-SNS usage models grounded in affordances.

8.1 Heuristics vs. Affordances-based Modeling

Every SNS is a toolkit that mixes features for posting, audience management, and policies in different ways. If people were to systematically assess the suitability of each available SNS every time they wanted to post something, it would require unwieldy time and cognitive effort. However, prior work has shown that people do not always make media usage decisions based on a systematic assessment of their choices. Rather, they make them based on heuristics [22]. Heuristics are automated cognitive processes that circumvent the conscious deliberation of information. Heuristics conserve cognitive energy and facilitate decisions, but they can be brittle in the context of new information or evolving situations. For example, when a new feature is added to a SNS, it changes how people post content, thus making it harder to rely on established heuristics about this SNS without first updating them.

Building an intelligent system that can match a communication goal with an SNS based on affordances is an alternative to heuristics-based behavior, and may support human decision-making when heuristics break down or are incorrectly applied. Ackerman [2] uses the term "critic" to describe such a system: "small agents that make suggestions to users...do not take action on behalf of the user; instead, they might offer warnings to the user." While heuristics and prediction systems offer the same benefits—automation, and consequently, reduced cognitive effort—there are some key differences between them that have practical implications.

The benefits of an intelligent system over heuristics are twofold: (1) people do not have to systematically consider their choices, and their SNS selections are not biased by prior use (i.e., they can take advantage of all SNSs in their ecosystem rather than always posting to the same set); (2) people can continue to post to appropriate SNSs even in cases when their heuristics need updating e.g., for a new SNS feature) or when they do not have established heuristics yet (e.g., when a new SNS is introduced in their ecosystem). Since people cannot rely on heuristics in these cases, a "critic" can prevent them from making errors by systematically considering the new choices. This proposed intelligent system is where we see human-AI collaboration occurring in the social media ecosystem: by building an automated system that can predict posting decisions, we enable AI to support human decision-making in this space. However, the final decisions for posting and updating the AI's model rest with the humans, making this a collaborative effort towards decision-making.

8.2 Implications for Design: Intelligent Systems Grounded in Affordances

Our affordance-based prediction models have implications for systems that can intelligently route a given post to an ideal set of SNSs in a person's ecosystem. This intelligent system could ask people to input values needed by the routing model (this could be desired and anticipated affordances, and other explanatory factors identified by future work), and output the ideal set of SNSs for posting that content. More concretely, the intelligent system we envision would ask the user to input the affordances they desire to post something (for example, "share this image to my friends and family and automatically delete it after some time"), and the affordances they anticipate having in each of their SNSs (for example, "I can use Snapchat to share images and videos with my family and close friends, and the content automatically disappears after 24 hours"). These anticipated affordances need only be input every few months because they would likely not change every time a user posts content. Using these two sets of affordances, the router could output the ideal SNSs the user should use to post their content.

Other than the SNS-centric benefits of such a system outlined in the previous section, its affordance-based nature provides two additional benefits. First, it would be privacy-preserving in that predicting ideal SNSs for posting based on desired and anticipated affordances does not require people to share their actual post with such a system. This is an important consideration for designing intelligent systems in general: we should ensure that people do not have to share their content, for SNSs or otherwise, anywhere but the intended place. Second, relying on anticipated affordances means that an important part of the prediction model does not change frequently, thus requiring only a small amount of information (about desired affordances) from people for each decision point. This ensures that we are saving them time and cognitive effort, while enabling their social needs and communication goals.

Heavy users of SNS ecosystems (i.e., people who use them frequently) would benefit from these kinds of intelligent systems in that they could engage in cross-site sharing without having to manually select all appropriate platforms, which is the current cross-site sharing state-of-the-art and is quite cumbersome. Additionally, researchers [40, 41, 45] have noted that social media literacy is a growing concern, especially among certain disadvantaged or less tech-savvy populations. Learning from population-wide usage, intelligent systems could assist low social media literacy individuals in finding appropriate networks for a given communication goal and warning against inappropriate ones.

Our affordance-based models and the resulting F1 scores obtained are an initial exploration towards enabling these intelligent systems. Per our results, these models provide ~83% F1 score values, which are significantly better than the current baselines. More work needs to be done to understand how affordances might be supplemented by other factors that feed into SNS preferences. Our hope is that our model can be a starting point towards operationalizing concepts such as affordances for better AI support in these settings. As researchers work towards building models that quantify the various technical, personal, and social characteristics that are behind people's SNS usage, we can build systems that combine these models to achieve higher accuracy and provide people with systems that will have the aforementioned benefits.

9 LIMITATIONS AND FUTURE WORK

Our operationalization of the affordance perspective was motivated by guidelines from previous work. While our particular operationalization helped identify findings that shed light on SNS ecosystems, operationalizing affordances at a different level of granularity would also result in valuable findings. For instance, because we wanted to ensure that our operationalization was not SNS-specific, we could not observe dimensions related to SNS-specific phenomena, e.g., Instagram's unique image filters or Twitter's 280-character limit. Similarly, with our audience affordances, one could imagine separating an audience into "exclusive" and "non-exclusive" categories, e.g., a network that affords sharing with friends and a network that affords sharing with friends only.

We focused on posting decisions when modeling multi-SNS usage to provide some constraint to our exploration of this massive space. Previous work on SNSs has shown that information needs or social browsing are also important use-cases. Future work should examine how people use SNS ecosystems to satisfy these other needs, just as the literature has done with individual SNSs. A combined study of communication and information needs would provide a holistic understanding of the use of these ecosystems.

One limitation of our methodology is that the communication needs we test come from hypothetical scenarios. Further, our results about these communication needs are based on a survey that tested one hypothetical scenario per participant. While this scoping was necessary for our study (as explained in the Methods section), an investigation with real, complete data from each individual could provide interesting insight into which communication needs are applicable for SNS users and how they express these real needs. Our use of Amazon's Mechanical Turk as our survey platform presents a similar limitation. Our sample is not representative of the national and international demographic. Future work should study the impact of location and culture on SNS ecosystem use.

A key motivation behind our proposal for intelligent systems grounded in affordances was to reduce the time and effort burden on people for selecting SNSs. While affordance-based models reduce the cognitive burden on people, they do require some effort—people have to input their desired affordances for each post and periodically update their anticipated affordances for each SNS. Future work should consider ways in which affordance information could be derived automatically (e.g., predict and recommend desired affordances and have people simply check if the prediction is accurate).

Finally, our data only provided a static snapshot of people's SNS ecosystems. A temporal analysis of these ecosystems could lead to interesting theories and results about their existence and evolution. To that end, the data we collected was a snapshot of people's multi-SNS usage in 2016, and these trends might also have changed since. Applying our intelligent system approach should capture these differences and is an important line of future work.

10 CONCLUSION

In this paper, we explore the use of affordances as a means of building platform-agnostic models that explain people's posting decisions within their SNS ecosystems. We conduct a scenario-based survey ($N = 674$) to collect data about the affordances people desire when posting content and the affordances they anticipate in each SNS they use. Based on these affordances, we build two models that demonstrate that: (1) affordances can explain posting behavior with high precision and recall, and (2) using a machine learning model with affordances as features can lead to significant improvement in accuracy over an unweighted model. Our models significantly outperform all current baselines, demonstrating that they advance the state-of-the-art in predicting SNSs for posting. We conclude with a discussion of a practical application of our results: helping to create intelligent systems for reducing the cognitive effort required to share content within the ecosystem of social network sites available. Our results serve as a proof-of-concept—a new direction for intelligent systems grounded in affordances to better support people's fluid needs in a complex ecosystem.

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