Exploring Activity-Sharing Response Differences Between Broad-Purpose and Dedicated Online Social Platforms

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People often leverage multiple platforms to share activities they undertake in their lives, from music listening to eating. *Broad-purpose* platforms, which people use to share a wide variety of activities with a diverse audience, and *dedicated* platforms, which often focus on tracking and sharing a specific activity with connections with similar interests, both help individuals seeking social benefits from sharing their activity. Researchers designing systems for activity sharing have often reflected on whether to support sharing on dedicated or broad-purpose platforms, suggesting a need to better understand their relative utility. We collected and compared the responses received between 700,000 pairs of activity-sharing posts on four sets of broad-purpose and dedicated platforms across two domains: physical activity (Strava, MapMyRun) and creativity (Dribbble, Behance). Results showed that dedicated platforms were more likely to receive responses (likes and comments), and comments were more likely to be encouraging and refer to specific qualities of the activities being shared. We reflect on the tradeoff between sheer audience volume and likelihood of response, and discuss how to design prompts and templates into sharing features which better align with the norms of respective platforms.

CCS Concepts: • **Human-centered computing → Empirical studies in collaborative and social computing**; **Social media**.

Additional Key Words and Phrases: Activity Sharing, Social Networks, Social Awareness Streams, Online Platforms, Personal Informatics

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1 Introduction

People often turn to online social platforms to share activities that they accomplish, ranging from major life activities like graduations, travel, or births to more everyday activities like exercising, music listening, or craft projects. Sharing activities online can help people achieve benefits such as being held accountable to goals in-progress [68, 70], celebrating accomplishments [21, 43, 100], emotional support or encouragement [37, 93], motivating or informing others to pursue similar goals [7], seeking informational support from reliable sources [58, 82], self-presentation, or maintaining relationships with others [113]. With the rapid expansion of communication technologies, especially

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the prevalence of online social platforms, people have opportunity to reach their desired audiences and achieve their sharing goals more easily than ever.

Although people frequently use multiple social platforms concurrently towards different sharing and communication goals, such as direct messaging with close ties [54, 91], online forums for feedback and support [16, 84], and live-streaming for sociality [104], one dimension by which social platforms can be organized is by their *content diversity* - the amount of activity domains that a platform supports sharing. Many research and commercial social platforms focus on supporting conversation and socialization around a *dedicated* category of activity, such as creative work (e.g., Dribbble, Behance, DeviantArt, [46, 62]), physical activity (e.g., Strava, Nike Run Club, [66, 69]), health issues (e.g., MyFitnessPal, PatientsLikeMe, [32, 61, 78]), and hobbies (e.g., AllTrails, Vivino, [34, 48]). Many platforms instead support activity sharing without a specific focus, such as when using *broad-purpose* platforms including Twitter, Instagram, or TikTok. Given the prevalence of sharing in the modern day landscape of online social platforms, the research field has frequently speculated the relative utility of sharing with different kinds of audiences and through different social platforms [98, 112].

Importantly, research has pointed out benefits and concerns with sharing on both kinds of platforms. On broad purpose platforms, it can be easier to reach a large and more diverse audience, helping one to get larger response when needed, such as connecting weaker ties for social resources [35, 74], diverse opinions for instrumental support [111], or celebrating major accomplishments and inform or educate others [21, 89, 100]. However, the audience's diversity can make sharers subject to concerns of privacy and contextual collapse, and people might worry about oversharing or that the shared content might not be interesting or too trivial for a large audience [10, 29, 69, 74]. Dedicated platforms, on the other hand, can help with reaching audiences with similar interests, which lowers the barrier for activity-specific benefits such as receiving specific support, feedback, or advice, and building up connection among interested others [19, 46, 61]. In these platforms, people are often concerned that what they share will be subject to social comparison or negative self-perception given the highly-centered interest [62, 97]. Further, it requires effort to maintain an active dedicated community with an sufficient audience size within the platform [46, 79, 80].

While research has pointed to benefits and concerns that people have or experience when sharing on both types of platforms, there is a lack of understanding of how actual response differs when sharing activities. We specifically examine three dimensions of response difference, following a tradition of prior studies examining similar dimensions on a single platform [18, 29, 88, 89]. (1) *Response quantity*: if people tend to receive significantly less response on one type of platform, it can hinder the purported benefits of sharing. Given that people fear that broad-purpose audiences will not be interested in their activities [29, 69, 74, 95], understanding the relative response will help validate that fear and suggest a need for design approaches to remedy it. (2) *Impact of use of editing features*: prior work has suggested that editing activity text description or embedding images are helpful for broader audiences to understand the content [29]. Understanding the extent to which use of these features matter on dedicated sites, versus more holistically, can influence whether and how platforms encourage editing. (3) *Textual response features*: response in positive valence and higher topical relevance is considered beneficial in helping sharers to realize the anticipated benefits [6, 8, 10, 75]. If responses to activity sharing on broad-purpose platforms tend to be receive in more positive language and with higher relevance to the activities being shared, it suggests that the benefit of broader reach outweighs the concerns. In line with these three dimensions, we ask the following research questions:

- **RQ1.** How does a platform's level of content diversity influence the quantity of response people receive when sharing their activity?

- **RQ2.** How does use of editing features in activity sharing posts such as (a) embedded photos and (b) edited text influence the quantity of response that people receive across the platforms with different level of content diversity?
- **RQ3.** How does the textual features of response differ between broad-purpose and dedicated platforms?

To answer these questions, we compared responses received when sharing activity on dedicated and broad-purpose platforms based on their quantity, the influence of editing features, and their textual response features. We examined applications with social awareness streams, or feeds of messages from one's social audience, which are used across a variety of different applications [13, 73] and provide similar format of social response (e.g., commenting features, one-click responses such as likes). We examined two applications in each of two domains (*creativity* in Dribbble and Behance, *physical activity* in Strava and MapMyRun) as case studies. Each application contained dedicated social awareness streams, and supported cross-posting activity sharing to Twitter, a broad-purpose platform. Our dataset contains more than 700,000 pairs of cross-posts of activity sharing and their replies across seven years from 2015 to 2022. We specifically compared the response in three dimensions to understand their differences across the platforms. To address RQ1, we compared the quantity of response (amount of likes, comments, unique commenters, and the presence of conversation) through regression analysis. For RQ2, we compared the editing features' influence (edited text or embedded images) through regression analysis. For RQ3, we examined the differences of textual features of response through textual analysis, leveraging TF-IDF and log-likelihood ratio for topic relevance, and sentiment analysis for emotional valence of the responses.

Our findings demonstrated that, on average, posts made to dedicated platforms received more social engagement compared to their counterparts on broad-purpose platforms, receiving more likes and replies from more unique commenters. This confirms prior work demonstrating that activities shared with more use of editing features (e.g., edited text descriptions and images) receive more social engagement [29]. Expanding on this finding, our work shows that embedded photos in particular increase amount of response more on dedicated platforms, but the likelihood of response on broad-purpose platforms. We find that comments on dedicated platforms are more positive in valence and tend to include more supportive words and more specific commentary about the activity being shared, such as the level of accomplishment in physical activity or visual aspects of creative works. Conversely, posts to broad-purpose platforms focus on the sociality around the activity and were more likely to include words displaying evidence of people leveraging the different social mechanisms of the platform to connect or communicate with others.

Overall, our findings illustrate benefits and drawbacks of sharing on each platform, such as trading off sheer audience size with likelihood of engagement. We further suggest recommendations for incorporating social platforms into activity-tracking technologies, such as how to design prompts and templates which align with the norms of dedicated and broad-purpose platforms. Through this examination, we contribute empirical understanding of how quantity and textual features of response differs by a platform's level of content diversity, how these differences are influenced by the use of editing features, and recommendations of how designs for activity sharing can better align with each platform's respective norms.

2 Related Work

Examining platform differences in activity sharing first requires defining terminology around activity and differentiating social platforms. Our analysis expands on prior work around sharing on broad-purpose and dedicated social platforms, as well as multi-platform behaviors.

2.1 Defining Activity Sharing, Broad-purpose, and Dedicated Online Social Platforms

We define an *activity* that someone might share online as something that an individual has spent time and effort on within their life, which they later reference in content that they create and share on an online social platform. Activities are largely shared for goals like celebrating accomplishments around activities completed [21, 43, 100, 113] or sustaining motivation to continue the activity [71, 74, 100]. These motivations differ somewhat from other goals for sharing online which do not typically center an activity, such as asking a question for the purpose of getting it answered [67] or sharing a personal interest or opinion in order to facilitate a conversation or social bonding with others [105]. Examples of activities that people share online span a wide range of different domains, such as creative work and artistic creations [19, 34, 46, 63], physical activity [29, 48, 66, 69, 106], health or wellbeing [21, 61, 74, 78], music listening [47, 52, 92], and gaming [39, 50, 83]. General updates of events or milestones of significance in the sharer's life including graduations, age milestones, births, identity changes, professional development, or travel could all be classified under activity sharing [23, 38, 49, 89]. While prior literature has often considered activity sharing in the context of sharing of personal informatics data [21, 29, 82, 102], we broadly consider what "data" could be when sharing activities, highlighting how people include a diverse set of information when sharing activities including tracked data, text descriptions, or media content such as images and videos. Activities need not be "quantified" (e.g., miles ran, times a song has been played) when being shared, though many are.

Figure 1 illustrates how we sort platforms where activities can be shared based on their *content diversity*. Content diversity in platforms exists on a spectrum. We broadly classify platforms as either *dedicated* (e.g., with low content diversity) or *broad-purpose* (e.g., with high content diversity). This categorization adds a new dimension to Zhang et al.'s full Form-From model [110], expanding the "Content" theme.

Our distinction between dedicated and broad-purpose social platforms largely excludes platforms which aggregate shared content from across communities which might be more "dedicated" in nature. For example, Reddit offers an example of a platform where people regularly subscribe to multiple communities with a more narrow focus. Specific servers connected by the ActivityPub protocol (e.g., Mastodon instances) might center more dedicated topics, but the broader connection with the fediverse enables aggregation largely outside the scope of our definition.

2.1.1 Dedicated Platforms. *Dedicated platforms* focus on supporting sharing of one or a few specific kinds of activities, providing some topical consistency and tend to have less diversity of content shared within the platform. In doing so, the platforms often incorporate features that support undertaking the activity alongside the social features, such as Spotify including a "Friend Activity" feed within their music-playing app or GitHub having an activity trace amidst supporting repository management features. Many dedicated platforms include features tracking or documenting activities as well as sharing them, such as triggering a recording of a run on Strava or MapMyRun or uploading pictures from new creative projects on Behance. Some platforms support sharing a few types of activities, which we classify as having slightly greater content diversity. For instance, Github's activity feed largely highlights when someone pushes or commits to a repository, but other types of activities like making pull requests or asking and answering questions appear in the feed. Wikipedia activities consist of a user's edit log, article creation, and also the discussion they have on specific topics. Conversely, activities in Venmo are homogeneous, consisting only of financial transactions, and thus has lower content diversity.

While one might not explicitly "need" to have interest in a type of activity in order to create an account and curate a feed on a dedicated platform, we anticipate that the overwhelming majority of people would only do so if they were interested in the activity. For example, while someone

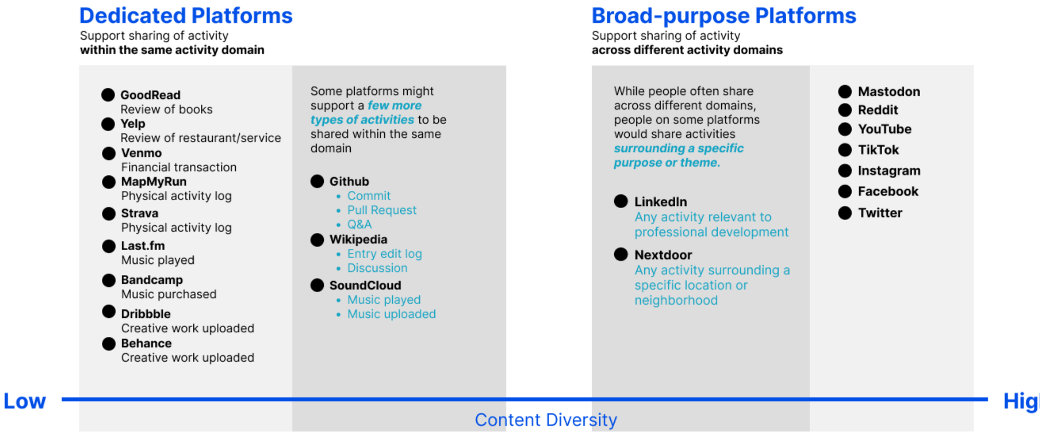


Fig. 1. Categorization of social platforms based on their *content diversity*. Dedicated, or low-diversity platforms, support sharing content within a single domain or among a few related domains. Conversely, broad-purpose platforms tend to have high diversity of content, supporting sharing many kinds of activities on the platform.

could create a Spotify account to follow what their friends are listening to, we imagine that the vast majority of people who use Spotify's social features also use the platform to listen to their own music or other content. We note that dedicated platforms may vary in how "central" the social components are to the platform's features. For many dedicated platforms, a person could document activities purely for their own reminiscence or self-understanding [86], and not share at all. But, others might view sharing as a more core component of the experience [21, 57, 72, 82].

2.1.2 Broad-purpose Platforms. Broad-purpose platforms, on the other hand, refer to social platforms that are without a focus or dedicated to a specific topic. Broad-purpose platforms include Instagram, Twitter, Facebook, TikTok, and Snapchat, and are often used to share a wide variety of topics with audiences. The specific platforms we consider as broad-purpose platforms have significant overlap with other common terminology surrounding social computing like social networking sites [9] or social media [44, 113], and are often the most widely-used social technologies.

Broad-purpose platforms have a wide variety of content, potentially including content which might not be classified as activities (e.g., opinions, news, asking and answering questions). These platform's sharing features typically do not limit or specifically encourage sharing a specific type of content. Different people can engage with radically different content on broad-purpose platforms, and there is no enforced consistency in the kinds of activities people engage with. While one user may use Twitter or TikTok to post when they go running, and follow other runners (or have their feeds algorithmically curated to show them content from other runners), another may instead use these platforms to share the music they are listening to and engage with others listening to the same music. Reddit and its subcommunities operate similarly. While an individual may curate the Subreddits they follow around particular interests or activities, the overall platform does not restrict or suggest sharing a particular kind of content.

Some broad-purpose platforms maintain high content diversity while still having focus on a specific purpose or broad topic. For instance, content on LinkedIn is typically professional in nature, but the platform enables people to share a wide range of professional activities including career moves, job postings, networking events, development training, and product or service launches. Nextdoor users also share many different activities relevant to their geographical proximity such as neighborhood events, yard scales or giveaways, and new rentals or subleases. We classify these platforms as having more content diversity than dedicated platforms, but less than other broad-purpose platforms.

2.2 Comparing Activity Sharing on Broad-purpose and Dedicated Social Platforms

People share activities that they undertake to achieve a range of sharing goals. Sharing activities can often help people receive the support they desired, including emotional or instrumental support [22, 25, 46, 51, 58, 61, 66, 74, 93]. Sharing activity with others could also help keep individuals motivated or hold them accountable to goals they have set [21, 68, 70]. People also often leverage this sharing as an opportunity to motivate their audiences to undertake the same activity [7, 20, 66]. In addition, sharing activity can also bring social-emotional benefits such as increasing a sense of connectedness [36, 54, 102], or fulfill people's communication goals around impression management or self-presentation [63, 74, 113].

In order to account for these different sharing goals, people often choose among different platforms to identify which would be most effective towards their sharing goal [76, 96], as well as cross-post to multiple platforms in order to reach different audiences at once [14, 33, 99]. Many research and commercial systems, including those which we study here, allow for sharing on both dedicated and broad-purpose platforms [28, 69]. In the context of activity, many apps for monitoring or performing activities include app-internal social platforms, while also supporting export of activities to broad-purpose platforms [57].

In our work, we examine how content diversity influences how three aspects of response: (1) the quantity of response people receive, (2) how using editing features impact the quantity of response, and (3) the textual features of the response people receive. Each of these measures relate to how people perceive whether they achieve their goal(s) for sharing activity.

2.2.1 Response Quantity. The amount of response received when sharing (e.g., replies, single-click response such as likes and favorites) is often considered by the sharer to be an indicator of the audience's interest in them and their content. For instance, the amount of response is often considered as an effective indicator of social support [4, 12, 87]. It also matters when people seek to celebrating life events or for social connections because past work uncovered that the quantity of response has been an indicator of fulfillment of people's needs for connections with friends, like-minded people, or support when sharing on social platforms [90, 101]. People also consider the amount of response as an indicator of success when seeking information or exchanging knowledge [55, 77] and requesting advice or critique, such as of creative work [62, 108]. At a platform scale, the amount of response that shared content receives is used as an indicator of the online community's health [6, 103], as having good amount of members actively interacting and socializing suggests that people are able to acquire sustained support and achieve long-term benefits from participating [111].

There are reasons to believe that response quantity could be higher on either dedicated or broad-purpose platforms when sharing activities. On broad-purpose platforms, people are able to reach a larger audience given the wide range of interests covered on the platform [11]. Consequently, users of the platform may often have many connections that they have different types of relationships or strength of ties with [76]. Sharing activities on platforms with larger audiences might make it more likely that the content to receive responses [111]. Conversely, for dedicated platforms, people are more likely to reach audiences with similar interests [19, 34, 46, 60, 61, 78], who might be more likely to provide response. In addition, the lower level of content diversity may lead to people more willing to share frequently [37, 46, 48], or to self-disclose [49, 106, 109], which often effectively helps individuals receive greater response or support [10, 23].

Research hypotheses: Based on previous research, we speculate that dedicated platforms, which provide an audience group that shares similar interests in a specific type of activity, could be helping the sharer to receive more response compared to sharing on broad-purpose platforms. We therefore hypothesize that:

- **Hypothesis 1.** Activity posts on *dedicated platforms* receive more response than on *broad-purpose platforms*.

2.2.2 Impact of Use of Editing Features. Because activities are often tracked in dedicated apps, there is often a "default" format applied when activities get shared, whether on dedicated or broad-purpose platforms. Shared activities from these apps typically consist of some text description of the activity and potentially an image, video, or other piece of media (e.g., a map for physical activity). Platforms often provide editable placeholders, such as of the text (e.g., "Afternoon Run" for Strava, "[Work Name] by [Author Name] for Behance) or of images (e.g., a map or a route ran on Strava).

Past research has pointed out that alignment with the interests of an online community tends to lead to more response received [6]. Individuals often reframe content to align with community norms [74] in order to receive their desired sharing outcomes. In activity sharing, editing features are a common design strategy for supporting people in reframing shared activities to add context. Prior work has repeatedly shown that how content is framed (e.g., inclusion of pictures, user-generated text) influences response [19, 24, 29, 46], and specifically that use of editing features leads to more response and higher impressions of the sharer when sharing physical activity from RunKeeper on Twitter [29]. However, studies typically examine the influence of editing features in a specific social platform, whether dedicated [19, 46] or broad-purpose [24, 29]. Understanding the relative importance of editing features in dedicated and broad-purpose platforms can influence design of these social features, such as requiring that content be edited on broad-purpose platforms.

Research Hypotheses: Given past analysis has suggested that using editing features result in greater response when used in one activity domain (*physical activity*) on a single platform (a *broad-purpose* platform, with high level of content diversity) [29], we expect that this effect will hold across sharing in different activity domains and platforms with different levels of content diversity. We further expect that use of editing features would cater more to the needs of dedicated groups (e.g., groups with shared interest in the activity, but low content diversity), as they might desire having more context around the activity. However, we expect that the influence of using editing features will be dwarfed by the effect of the platform's content diversity. Said differently, we expect that audience matters more than the content. For example, switching from a broad-purpose platform to a dedicated platform might boost the amount of likes and comments received more than using editing features to embed user-generated photos when sharing a physical activity. Therefore, we hypothesize that:

- **Hypothesis 2-1.** Using editing features results in higher likelihood in receiving response as well as more responses.
- **Hypothesis 2-2.** Response amount is influenced more strongly by a platform's level of content diversity than the use of editing features.
- **Hypothesis 2-3.** Use of editing features to change text increases response amount more on dedicated platforms than on broad-purpose platforms.
- **Hypothesis 2-4.** Use of editing features to embed photos increases response amount more on dedicated platforms than on broad-purpose platforms.

2.2.3 Textual Response Features. Beyond response quantity, people who share often value aspects of the quality of the response received, such as whether it aligns with their sharing goals. One common strategy for assessing textual quality is to examine the emotional valence of response, as this impacts how people perceive the support they receive. Studies of online communities suggest that use of positive language in posts and replies can lead people to feel connected to one another and reciprocate positivity [17], as well as sustain motivation in activities that requires substantial effort such as fan-fiction writing [15]. Valence in response also heavily impacts participation in online communities [114]. Receiving positive response further helps individuals enhance their emotional well-being in online sharing contexts [5, 10]. Furthermore, research has suggested that there a is a contagion effect to positivity in online communities, where people who receive more positivity are more willing to further provide positive comments to others [18]. Topical relevance of the response also has great impact on how individuals perceive their sharing response because it reflects the audience's interest in what was shared [8]. The response not staying on topic could lead to incoherent conversation, which can diminish the individual's willingness to participate in the online platform in the future [6].

Past work suggests that response valence might be higher on dedicated platforms because people are often willing to self-disclose more in these spaces [49, 106, 109], and greater self-disclosure disclosure of emotion can lead audiences responding with more emotion [10]. Broad purpose platforms may also have established norm of responding to activities positively, but this may be caused by more of a norm of sharing positivity and performing identity [41, 113]. Towards topical relevance, as dedicated platforms have less content diversity, people might be more likely to stay on-topic when engaging and responding to shared activities [99]. Moreover, audiences on dedicated platforms likely share higher interest in the topic, thus leading to them more likely to provide relevant comments based on their interest and knowledge. Conversely, it may be less likely that audiences on broad-purpose platforms have relevant comments to share about the activity.

Research Hypotheses: Based on the prior work, we expect to see comments on dedicated platforms having more positive valence because the amount of topical understanding will lead to greater support. We also expect to see higher topical relevance in responses on dedicated platforms because of the shared interest in the domain. For instance, people sharing physical activity on a dedicated platform might be more likely to get response that focus on the details about the activity. Therefore, we hypothesize that:

- **Hypothesis 3-1.** Activity posts to *dedicated platforms* tend to receive more response in positive valence than their counterparts on *broad-purpose platforms.*
- **Hypothesis 3-2.** Responses to activity posts on *dedicated platforms* tend to have more topical relevance than their counterparts on *broad-purpose platforms.*

3 Method

To answer our research questions and test our hypotheses around the influence of platform's level of content diversity on response when sharing activity, we sought to examine how the quantity and characteristics of responses differ across platforms. Doing so required identifying dedicated platforms where activities were frequently cross-posted to a broad-purpose platform, collecting and filtering posts to those platforms, and analyzing the responses. We further discuss ethical considerations of our approach.

3.1 Identifying Platforms

To address our research questions around comparing the responses on broad-purpose and dedicated platforms for sharing data-driven activities, we first identified platforms suitable for conducting this analysis.

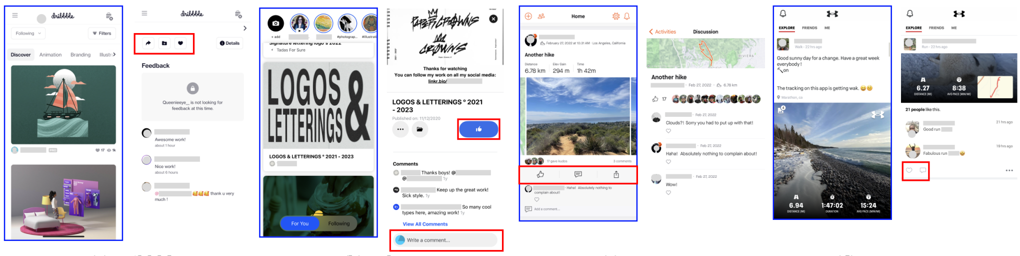
Towards a broad-purpose platform, we aimed to identify a platform that (1) did not have a clear focus on a type of activity, (2) prioritizes social interaction through a social awareness stream [73], (3) has an active user group that would cross-post from dedicated platforms, and (4) provides social features that allows audience members to provide feedback in the form of text and one-click response [40]. We chose Twitter as our focus as it fulfills all above inclusion criteria, but other prominent platforms such as Instagram have similar features. In particular, Twitter's now deprecated [3] API resources for academic research, were free and openly available for researchers during the time of our data collection, and enabled collecting public conversation data on the platform needed to answer our research questions [1].

For the dedicated sharing platforms, we aimed to identify platforms that focus on a specific domain of activity sharing. As our goal is to compare the sharing responses between broad-purpose and dedicated platforms, we sought dedicated platforms that support exporting the shared activity to broad-purpose platforms while also having similar social features for responses within the dedicated platform, particularly text comments and one-click responses. We therefore identified dedicated platforms which: (1) allow people to share activities that include additional complementary information, such as images, text, or personal tracked data (2) include a social awareness stream system similar to their broad-purpose platform counterpart that allows its users to both provide comments in text and click to response (e.g., like, give heart, or "+1") on others' shared activity (3) explicitly supports exporting to a broader social platform when finishing the activity, e.g., a "share to Twitter" button either at the end of the sharing process or from within the options for a post.

Implementation details associated with a specific application are likely to impact people's sharing behavior and responses towards our research questions. For example, some domains of activity may be more suitable towards sharing on broad-purpose platforms, applications differ in exactly how they implement social awareness streams, and social norms are likely to develop within dedicated communities. To mitigate the impact of any application-specific characteristics, we decided to conduct our analysis across multiple dedicated applications and compare our results. We identified two different applications in two different domains which met our inclusion criteria. We considered and investigated a range of domains popular for activity sharing including music sharing (e.g., Spotify, Last.fm, Soundcloud, 8Tracks), diet and food (e.g., MyFitnessPal, Foodgawker, Yummi), finance (e.g., Venmo), physical activity (e.g., Hevy), and creative work (e.g., DeviantArt). Several applications were considered, but eventually excluded from our study due to having limited cross-posting support (e.g., Hevy, Yummi), not supporting social engagement such as commenting (e.g., Foodgawker), does not fit our definition of activity sharing (e.g., Soundcloud, where Twitter cross-posts were not personal activity-sharing but rather self-promotion). We settled on *physical activity* and *creativity* as two prominent domains for sharing personal data [27] where we could identify two dedicated platforms (Strava & MapMyRun for physical activity, Dribbble & Behance for creativity) which met our inclusion criteria.

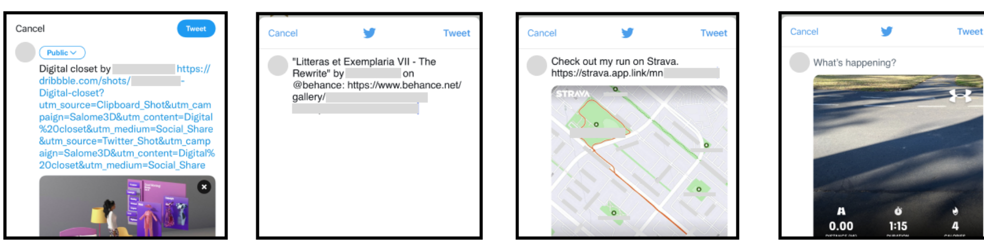
3.1.1 Differences Between Selected Platforms. All four applications we selected shared a similar social awareness stream with similar social support features. All allowed audience response in the form of likes and replies. Though similar, there were slight differences on how information were presented and social features were designed on their corresponding "social feed". Figure 2 provides examples of activity posts to each social feed, and figure 3 shows how activities look when cross-posted to Twitter. Table 1 describes differences between applications and how they support sharing to broad-purpose platforms like Twitter.

The applications vary slightly in the level of information displayed in the main feed (Figure 2). In Behance's feed, for example, only images, title, and author were presented without any social



(a) Dribbble (b) Behance (c) Strava (d) MapMyRun

Fig. 2. Example of social feeds on each dedicated platforms. Social feeds (left, in blue frame) on each platforms differs with the information presented and where they enable platform user to engage with their built-in social features (in red frame) to provide likes and comments.



(a) Dribbble (b) Behance (c) Strava (d) MapMyRun

Fig. 3. Example of editing screen when cross-posting to a broad-purpose platform (Twitter) from each dedicated platforms. Each application provides different edit support.

metrics. All other applications all displayed social engagement metrics for each post in their feeds. How one leaves social feedback also differs slightly between applications. Strava had the most accessible social features among all dedicated platforms, offering buttons for giving likes and replies directly in a user's social feed. All other dedicated application requires the user to click into each activity sharing post in order to provide likes and comments. Behance provides some additional friction, requiring a user to scroll down to the bottom of the activity post to leave comments. As the broad-purpose platform we studied, Twitter displayed social engagement metrics and allowed liking and commenting on its user's feed. Our analysis only considered metrics and features that were shared among all application and platforms. There were also minor variations across the applications, such as differences in terminology across the platforms (likes were "kudos" on Strava) or name-tagging in replies available only on Dribbble, Strava, and Twitter. Some applications also provide alternative engagement features, such as Twitter's "retweeting" of a post, which we did not consider in our study. Though there are differences within how applications generate friction when leaving social feedback, we did not notice these differences impacting like or response rate in the applications we studied.

Applications also provide different editing features for posts, differing on two aspects: (1) what fields were required for each post, and (2) whether default templates of text, stock photos, or text prompts were provided. Some dedicated applications required images (Strava, Dribbble, and Behance) when sharing activities while others did not. Some platforms offer text prompts that help formulate written descriptions (Strava, Dribbble, and MapMyRun) while others (Export-to-Twitter on Strava, Dribbble, and Behance) offer default text templates. We also highlight the differences

Application	Type	Main Text Field Required	Main Text Field Edit Support	Main Text Field Prompt / Template Example	Images Required	Images Edit Support	Images Description
Dribbble	Dedicated	Yes	Text Prompt	"Give me a name"	Yes	Text Prompt	"What are you working on? Upload your design. This will also be used as the thumbnails in feed"
	Broad-purpose	No	Text Template (Auto-filled)	"[Work Name] by [Author name] http://[link-to-Dribbble-activity]"	No	Default image	User-uploaded image from activity post
Behance	Dedicated	Yes	Text Prompt	"Name Your Project"	Yes	Text Prompt	"Start a Project / Add content to your project using the tools below"
	Broad-purpose	No	Text Template (Auto-filled)	*"[Work Name]" by [Author name] on @Behance http:// [link-to-Behance-activity]*	No	No Prompts or Default image	No default image
Strava	Dedicated	Yes	Text Template (Auto-filled)	*"Afternoon Run"*	Yes	Default image (Auto-filled)	Image of map template of tracked activity route
	Broad-purpose	No	Text Template (Auto-filled)	"Check out my run on Strava! http:// [link-to-strava-activity]"	Yes	Default image	Image of map (default), or user-uploaded image overlayed with a summary of tracked data
MapMyRun	Dedicated	Yes	Text Template (Auto-filled)	*"00:00:01 Run"*	No	Text Prompt	"Add Photo"
	Broad-purpose	No	Text Prompt	"What's happening?"	No	Text Prompt	"Share the highlight. Add a cover photo". Photos added are overlayed with a summary of tracked data

Table 1. Summary of features present in each platform in our study. "Broad-purpose" implies how each dedicated platform surfaces the editing features in the interface for cross-posting to Twitter, the broad-purpose platform in our study. All platforms provide some form of text template, while many include a default image.

between encouraging or requiring adding photos when sharing activity. Table 1 describes support for different editing features across each application.

3.2 Data Collection & Filtering

To compare the responses that people receive when sharing the same activities on both types of platform with different level of content diversity, we collected posts where a user shared the same activity on both broad-purpose and dedicated platforms by identifying cross-posts from dedicated platforms to Twitter. The dataset we collected consists of fields that the platform pair both included, including post metadata (id, text content, author, timestamp, amount of attached photos) and post responses (like counts, reply counts, reply contents, and accounts that replied). After filtering, our dataset includes over half a million cross-posted posts across the four applications.

3.2.1 Collection of Posts. To collect pairs of posts shared across the two types of platforms, we first started collecting posts on Twitter that were cross-posted from our chosen dedicated platforms. We identified these tweets through whether they contained both application-associated hashtags (e.g., #Strava, #Dribbble, #Behance, except for #MapMyRun) and a link to the shared activity on its dedicated platform counterpart (e.g., strava.com/activities) and collected the tweets by accessing the Twitter API endpoints. Our dataset includes cross-posts from November 2015 to February 2022 (see Figure 4). We filtered to posts which occurred after Twitter made a platform-wide change from "favorite" (clicking a star) to "like" (clicking a heart) a Tweet [2]. In addition to keeping framing of responses constant on the platform, this change aligned more closely with the features present in the dedicated platforms. For collecting the corresponding activity posts on the dedicated platforms, we back-tracked to the dedicated platforms posts using the links in the collected tweets, similar to prior work [24].

After collecting the data from the dedicated platforms, we filtered out posts which were not accessible or relevant for analysis. First, we removed tweets with links to dedicated platform

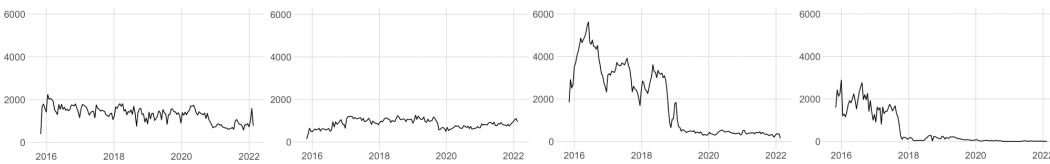


Fig. 4. Distribution of cross-posts collected for each application in time. Our dataset contains cross-posts from dedicated platforms to Twitter from between November 2015 and February 2022.

activities which were inaccessible. Some were dead links, as well as links where like/comment data on the dedicated platforms were inaccessible, potentially because of the account's privacy settings on the dedicated platform. We also removed shortened links (e.g., IFTTT links) which were more difficult to automate the collection of. Second, we removed tweets which had links to dedicated platform activities that were obviously not examples of activity sharing, such as "challenges" on Strava. Third, when a person cross-posted an activity multiple times (e.g., re-shared the same creative work link), we kept only the chronologically first post and tweet to minimize influence of reposting on our analysis, as interest in repeated posts from an individual on a single topic might diminish over time.

To minimize the influence of bot behavior (e.g., bot-generated activities) on our analysis, we also examined the frequency and style of posts in our dataset. To achieve this, we first identified accounts that fit the following criteria: 1) accounts which tweeted more than 25 tweets in the dataset 2) accounts which had more than 75% of their tweets created within 30 days of each other, or 3) accounts which had more than 50% of their tweets referencing the same activity on the dedicated platform. In addition, we identified the posts from the 25 most prevalent posters in each domain, which accounts for 6.55 to 18.69% of each overall dataset. We manually examined the posting history of these accounts to determine whether they are bots. Our manual inspection focused on whether the post frequency seemed reasonable (e.g., even the most prevalent users tended not to run or post creative works more than once per day), whether the post content seemed repetitive, or whether timing seemed synchronized or otherwise suspicious. Within the category, we found some accounts that appeared to be "influencers" [45, 56] on the platforms by posting frequently and accruing a large following, but otherwise follow posting behavior in frequencies similar to other users.

After our manual inspection, we found accounts from both Dribbble and Behance that self-described as bots in their account description, and do not follow normal posting patterns by posting links to activity of creative works from other account. We removed the activities posted from these accounts to help preserve the validity of our dataset. Overall, platforms varied in frequency in use over time, with MapMyRun having significantly fewer cross-posts after 2018, Strava reaching a lower but steady number, and Behance and Dribbble remaining more constant throughout the duration of data collected (Figure 4). Our data collection lasted three months, spanning May 2022 until August 2022), leading to the collection of a total of 951,481 pairs of posts, meaning that all posts had nearly three months to accrue responses prior to inclusion in our dataset. After the aforementioned filtering criteria, our final dataset consists of 728,759 pairs of posts.

3.2.2 Collection of Comments. To answer RQ3 on how the textual features of response differs across platforms, we collected replies or comments to the posts on each pair of platforms. On MapMyRun, comments and comment counts were not publicly accessible for large scale data collection, so our analysis of comments focuses on the other three applications. Although we were able to collect the number of replies for all posts to the other three platforms (Strava, Behance, Dribbble), technical limitations in each application (e.g., pagination and infinite scrolling in posts which have many comments) limited our ability to access the full set of comments for each activity sharing post. Due to such constraints, we were only able to collect the text of the first 10 replies within each application, both for dedicated and broad-purpose platforms. To verify that further replies were similar in nature to the 10 we were able to collect, we manually inspected all comments for 100 posts across each of the three applications where we analyzed comments. We confirmed that further replies were linguistically similar, such as offering support in similar terms or continuing a back-and-forth conversation between the person who completed the activity and a member of their post audience. However, we decided not to examine the comments on posts with greater than 10 replies as part of our linguistic analysis, which consists of 3.86% of the posts we examined in total. While it is a limitation that our data does not include all comments in response to posts, excluding these comments has the benefit of minimizing the influence of comments to posts which received many responses (e.g., comments on influencer accounts) in our analysis.

To check for bot comments, we further examined accounts which posted identical comments in response to at least 25 posts. We manually inspected the comment content to confirm they were bot accounts, finding that they typically used these comments to advertising their businesses or to promote specific events like races. We removed such bot comments from our analysis. In total, we collected comments from a total of 700,599 pairs of posts (out of the 728,759 pairs of posts from our dataset) that consist of a total of 810,301 comments (out of 3,465,729 comments from the total comments in our dataset).

3.3 Descriptive Analysis of Dataset

Overall, our dataset includes over 700,000 paired posts, with Strava contributing the most (over 300,000) and MapMyRun contributing the fewest (about 88,000).

Platform	Total Posts	Content Diversity	Has Photo	Has Edited Text	Has Likes	Likes (Mean)	Has Replies	Replies (Mean)	Has Conversation	Has Unique Commenters	Commenters (Mean, Max=10)
Dribbble	202,681	Broad-Purpose	13.20%	56.08%	47.18%	1.54	8.29%	0.12	2.87%	6.92%	0.16
		Dedicated	99.80%	90.27%	95.03%	119	54.99%	4.15	10.46%	38.10%	1.45
Behance	133,752	Broad-Purpose	28.02%	75.95%	46.70%	2.57	10.94%	0.19	4.99%	9.72%	0.24
		Dedicated	97.96%	58.10%	89.90%	27.62	50.87%	1.18	12.89%	48.97%	0.90
Strava	304,102	Broad-Purpose	49.55%	57.07%	42.98%	1.14	15.50%	0.20	4.51%	7.46%	0.11
		Dedicated	33.98%	70.06%	83.71%	11.93	19.42%	0.53	11.74%	18.19%	0.29
MapMyRun	88,224	Broad-Purpose	0.26%	42.73%	29.25%	0.47	5.45%	0.07	-	-	-
		Dedicated	2.02%	35.37%	46.01%	0.56	35.41%	0.07	-	-	-
Average	182,190	Broad-Purpose	22.76%	57.96%	41.53%	1.43	10.05%	0.14	4.12%	8.03%	0.17
		Dedicated	58.44%	63.45%	78.66%	39.78	40.17%	1.48	11.70%	35.09%	0.88

Table 2. Descriptive Statistics for each platform. We present the percentage of posts that contain the engagement metric (e.g., what proportion of posts have at least one like) or editing feature (e.g., what proportion of posts where text has been edited), and the mean of the engagement metric (e.g., how many likes on average).

3.4 Analysis

Following the collection of posts and comments across the platforms, we analyzed the dataset statistically and linguistically to uncover the differences between the activity sharing on platforms with different level of content diversity. Here we describe the approaches that we took and present the measurements we derived from these approaches.

3.4.1 Analysis of Response Quantity and Impact of Using Editing Features. To answer RQ1 and RQ2, we aimed to understand the differences in response between activity posts shared on the platforms with different level of content diversity. We therefore identified features of activity sharing posts as the independent variables, and the measurement of responses as dependent variable. We chose the variables that were present in both platforms for alignment in observation, thus excluded post features such as achievement counts and response metrics such as amount of retweets.

Activity sharing posts were first marked for the *level of content diversity of the platform* it was shared on and whether it contained edited content from the sharer. We accounted whether a post included *embedded images*, and if they were edited to include *edited text* content, as these measures have been shown to have significant effect on sharing outcomes and perceptions of shared content in previous work [29]. To identify whether a post contains edited text, we first manually inspected the text fields of posts in the dataset for each platform and generated a list of default text patterns. For instance, cross-posting Strava activity to Twitter contains a default text string such as "Check out my *[physical activity type]* on Strava. *[URL to the strava activity]*". We then iteratively filtered out posts that included these text patterns and randomly sampled the remaining posts for manual inspection to identify additional text patterns. For platforms which did not include default text patterns, we accounted for whether any text description were added to the posts. Examples of text that a user might add include, "Humid weather for a lunch run!" for a MapMyRun activity, or "Awesome case study" for a shared activity on Behance.

For dependent variables, we focused on the *responses* and *influence on responses* to understand how activity sharing is impacted by the platform's level of content diversity and edited content. We operationalize **responses** as the *likes* and *comments* each post received, the *amount of unique accounts that replied* to each post (excluding the original poster account), and whether a *conversation happened in the replies* of the post. We define the appearance of conversation in the replies as whether the original poster replied to a comments in the activity sharing for at least once (e.g., a post included at least one comment by someone other than the original poster, followed by at least one comment by the original poster). We operationalize the **influence on responses** as the effect size of independent variables on responses. For instance, how embedding photos in post boost the odds of having any responses or increase the amount of responses. Operationalizing responses in these variables enable us to further examine 1) whether a post receive any responses, and 2) the amount of responses a post received, and the effect size of an independent variable on 3) the odds of receiving any responses and 4) the amount of responses received.

For the three statistical analyses where the response was a count (e.g., number of likes, number of comments, number of unique user accounts who replied), we used a Negative Binomial model for regression analysis to characterize the correlation between the post features and each measurement of response. We switched from Negative Binomial model to Poisson model for a few responses in the dataset (commenters count for Strava, and replies count for MapMyRun) as the mean value of them were relatively close to the variance. A test for overdispersion further indicated the presence of excess zeros for likes, replies, and number of unique commenters, which intuitively follows from the number of posts with no response. For the zero component, we considered the impact of the platform, effectively analyzing whether the platform influenced the likelihood of getting a response altogether. We used a binomial model for regression on the zero part, characterizing the correlation between the platform's level of content diversity and the measurement of whether the shared activity received any response. We ran the Negative Binomial/Poisson component of the regression with the following equation, and followed up with pairwise comparisons to uncover the effect size of interaction effects with Bonferroni-corrected p-value adjustments after the tests:

$$log(y) = {}_0 + e_{1platform} + e_{2photo} + e_{3text} + e_4({}_{photo} * {}_{text})$$

However, for creative platforms, the presence of an image was highly correlated with the platform's level of content diversity. Nearly 98% and 100% of posts to Behance and Dribbble's dedicated platforms included images, respectively, with only 23-28% of posts to their broad-purpose counterparts including images. Running the above regression for the creativity platforms resulted in interaction effects which seemed largely characteristic of this correlation rather than meaningful insights into the relative utility of adding images to dedicated versus broad-purpose platforms. We therefore dropped the image terms from these regressions, resulting in a simpler and easier to interpret model.

3.4.2 Analysis of Textual Response Features. To further understand the differences of characteristic of responses between activity sharing on platforms with different level of content diversity (RQ3), we applied text analysis methods through three approaches to study the content of these responses. Our research approach to analyze text feature was inspired by past work studying community norm differences between two subreddit with similar theme [16] as our works similarly focus on social engagement differences between two online communities. To prepare the data for analysis, we first pre-processed the data to lowercase all words and removed stopwords, punctuation, emojis, and urls from the comments. We then employed n-gram language modeling to tokenize the comments. As our goal was to uncover patterns in general word usage, we filtered out non-english words in the comments. We also manually removed names from the comment data to prevent words specifically appearing on one of the platforms that could potentially skew the dataset. In particular, we noticed that the names of platform influencers often appeared in subsequent analyses of dedicated platforms (e.g., “Great job [runner]!”). Our three analyses were:

Sentiment Analysis: To understand the words used differently between the platforms with different level of content diversity, we conducted a sentiment analysis on all comments in each comment corpus for the platforms. Our goal was to identify whether there are tone differences between the platforms for the responses that people received when sharing activities. We used Valence Aware Dictionary and sEntiment Reasoner (VADER) [42] as our sentiment analysis tool, given the tool's utility for analyzing short social media data. With VADER, we calculated the positive sentiment score which represent the extent each comment leaned towards a positive sentiment. We focused on positive sentiment because we expect that comments would be largely supportive or encouraging of the person who shared the activity. Early analyses of sentiment verified this, with comments on very few tweets or posts to dedicated platforms including any negative sentiment (less than 10% of the dataset included any negativity).

TF-IDF Analysis: We applied the term frequency-inverse document frequency metric (TF-IDF) to identify important linguistic tokens while also minimizing the influence of frequently used operational or function words in the dataset. We conducted TF-IDF independently for each application. In our case, the value of each word increased proportionally as it appears in each comments, but would be offset by the frequency of the token in the entire comment corpus collected from a platform. Similar to Chancellor et al. [16], we use this TF-IDF analysis to form the basis of a comparison between two similar platforms with key characteristic differences.

Log Likelihood Ratio (LLR) Analysis: We examined the differences in comment content between the platforms across the three platform pairs for which we collected comments from (Strava, Dribbble, and Behance). Through computing the Log Likelihood Ratio (LLR), we were able to identify the most distinct and most similar words between two corpora. LLR is calculated as the logarithm (base 10) of the ratio of the probability of a word's occurrence in the dedicated platforms' corpus to the probability of it's occurrence in the broad-purpose platforms' corpus, followed by normalization using the maximum frequency value within each corpora to prevent the difference size of corpora from skewing the result. Our calculated LLR values fall between 1 and -1, where large positive values imply that the word is more frequent in comments on the broad-purpose platform while negative values means the word appears more frequently in comments on the dedicated platform. By sorting words and filtering to the highest and lowest LLR values, we can identify which words commonly occurred on one platform, but not the other.

3.5 Ethical Considerations

During our data collection process, we highlight several approaches that we took to protect the privacy of users who shared on the platforms that we collected data from. First, we only accessed posts which were available to all users of the platform regardless of social relationship with the person sharing (e.g., did not have to be friends or friends-of-friends) in respect of the user's privacy preference settings. We only used user identifiers for filtering and pairing the posts while filtering out and pre-processing for the dataset. We focus our results only on aggregated posts, and do not report on the content of specific posts people made when conducting data analysis. All specific examples of activity sharing posts in the methods or in other sections are paraphrased from common posts we saw.

We took care to ensure that the mechanisms we used to automate collection of activity posts were as close to human-like as possible. We made sure to follow each platforms' publicly-posted rate limits for accessing posts to avoid overloading the platform's servers with queries. We also instituting a timeout to resume collection after hitting rate limits of the application, such as 15 minutes for collecting from Twitter. These considerations effectively capped the number of tweets and posts to dedicated platforms which we could collect per day, resulting in us spacing out our collection across three months.

4 Results

In this section, we present the results of our analyses to address our research questions. To answer our first two research questions (RQ1 & 2), we first describe the results of regression analyses comparing the quantity of responses between dedicated and broad-purpose platforms. We also evaluate the effect of the level of content diversity, having images, and having edited text, and how using these two editing features moderates the effect of response. We then answer our third research question (RQ3) with results from content analyses on the differences in linguistic features of the response between the two types of platforms through TF-IDF and LLR on topical relevance, and sentiment analysis on emotional valence. All values within the tables of the following subsections were exponentialized, representing the expected effect in the original unit of analysis (e.g., increase in expected likes when on a dedicated platform versus a broad platform, increase in percent likelihood that a post has conversation if a photo is included, etc.).

4.1 RQ1: Influence of Level of Content Diversity on Responses

Our findings largely support the first hypothesis (*H1*) that sharing on dedicated platforms significantly increases the likelihood of receiving response and the response one gets across all apps. Our results also shows that sharing on dedicated platforms significantly increases the likelihood of getting any responses (across all apps except for MapMyRun) (Table 4-II). Aggregating and averaging across platforms, we observed that on broad-purpose platforms, an average of 40.72% of posts receive likes and 9.8% of posts receive replies, comparing to an average of 78.81% receiving likes and 41.36% receiving replies on dedicated platforms[1]. Furthermore, each post receive an average of 26.55 more likes and 0.825 more replies on dedicated platforms comparing to broad-purpose platforms. Sharing on dedicated platforms generate more likes (from 7 to 149 times more), replies (from 2 to 18 times more), receive replies from more commenters (from 1.1 to 1.89 times more), and

(I). Has Response: Whether Post received any response				
		Platform	Photo	Text
Dribbble	Like	**20.41**	-	2.07
	Reply	**17.10**	-	2.59
	Unique Commenter	**12.11**	-	2.78
	Conversation	3.32	-	**3.46**
Behance	Like	**12.15**	-	2.14
	Reply	**31.32**	-	7.74
	Unique Commenter	**23.53**	-	7.84
	Conversation	**11.96**	-	10.22
Strava	Like	**6.27**	1.74	1.92
	Reply	1.63	**3.05**	2.20
	Unique Commenter	3.38	1.81	**3.87**
	Conversation	3.57	1.94	**3.86**
MapMyRun	Like	0.49	**2.85**	1.03
	Reply	0.72	**4.33**	1.14

(II). Response Amount: Amount of Response a Post Received				
		Platform	Photo	Text
Dribbble	Like	**51.74**	-	1.92
	Reply	**4.71**	-	1.32
	Unique Commenter	1.69	-	**1.72**
	Conversation	-	-	-
Behance	Like	**149.22**	-	5.31
	Reply	**18.67**	-	2.38
	Unique Commenter	1.59	-	**1.88**
	Conversation	-	-	-
Strava	Like	**7.22**	1.52	2.00
	Reply	**2.64**	1.14	1.35
	Unique Commenter	1.10	0.98	**1.34**
	Conversation	-	-	-
MapMyRun	Like	1.38	**2.03**	1.46
	Reply	**1.35**	1.06	1.19

Table 3. **Regression results (for RQ1 & 2, H1 and H2-2)**: (I) whether the post has any responses as social engagement and: (II) the amount of responses as social engagement (only on posts that have at least one response) showing the effect of (a) *Level of Content Diversity* (b) *Having Embedded Photos* (c) *Having Embedded Edited Text*. The coefficient values are the effect size of when applying each factor to share. All results marked were Statistically significant (p < 0.0001). **Bold** values are the largest across factors. We only account for the main effect, thus excluding *Photo* on creativity domain.

are more likely to lead to conversation in their replies (from 3.57 to 11.96 times more) comparing to broad-purpose platforms (Present in Table 4-I).

4.2 RQ2: Influence of Using Editing Features on Different Platforms

(I). The Use of Editing Features on **whether a post received any response**					
		Photo		Edited Text	
		Broad	Dedicated	Broad	Dedicated
Dribbble	Like	-	-	**2.07**	1.69
	Reply	-	-	**2.59**	1.54
	Unique Commenter	-	-	**2.78**	1.30
	Conversation	-	-	**3.46**	1.58
Behance	Like	-	-	2.14	2.25
	Reply	-	-	**7.74**	2.25
	Unique Commenter	-	-	**7.84**	1.75
	Conversation	-	-	**10.22**	1.92
Strava	Like	**1.74**	1.40	1.92	**2.83**
	Reply	**3.05**	1.71	2.20	**2.57**
	Unique Commenter	**1.81**	1.68	**3.87**	2.86
	Conversation	**1.94**	1.64	**3.86**	2.91
MapMyRun	Like	**2.85**	1.43	1.03	**1.70**
	Reply	**4.33**	1.52	1.14	**1.52**

(II). The Use of Editing Features on **the amount of response a post received**					
		Photo		Edited Text	
		Broad	Dedicated	Broad	Dedicated
Dribbble	Like	-	-	**1.92**	1.21
	Reply	-	-	1.32	**1.42**
	Unique Commenter	-	-	**1.72**	1.02
Behance	Like	-	-	**5.31**	2.17
	Reply	-	-	**2.38**	1.56
	Unique Commenter	-	-	**1.88**	1.20
Strava	Like	1.52	**1.61**	2.00	**2.14**
	Reply	1.14	**1.20**	1.35	**1.65**
	Unique Commenter	0.98	**1.08**	1.34	1.28
MapMyRun	Like	**2.03**	1.19	1.46	1.18
	Reply	1.06	1.09	1.19	1.23

Table 4. **Regression results (for RQ2, H2-1, H2-3, & H2-4)**: Comparing *predicted estimated marginal means* shows the effect of using editing features (to embed Photos or edit Text) on (I) whether the post has any responses as social engagement and (II) the amount of responses as social engagement across platforms with different level of content diversity. The coefficient values are the effect size. **Bold** values are the largest between the two platforms and all results marked, and were found to be statistically significant (p < 0.0001).

Aligning with findings from previous work [29], our analysis indicates that activity posts with greater levels of usage of editing features receive significantly more responses (more likes, replies, amount of commenters, and more likely to have conversation) on all platforms (Table 4-I.), as

[1]Reported comparison of means are all statistically significant at p < 0.0001. For brevity, we therefore do not report the result of each statistical test.

all values across applications (except for the effect of embedding photo on commenter counts in Strava's broad-purpose platform) were all larger than 1, indicating an increasing effect. We also see that adding photo and text increase the likelihood of getting any response on both platforms with different level of content diversity across all domain and apps that we observed. These results support our first hypothesis among the four we have for the use of editing features, that the use of editing features leads to higher likelihood of receiving response and more response (*H2-1*) (Table 4-II). For our second hypothesis (*H2-2*), we received mixed result comparing the effect size of switching between platforms with different level of content diversity and including edited content (Table 4-I). We find that effect size of level of content diversity are generally larger than effect size of edited content for creativity domain for both whether the post received any response or the amount of response (except for whether Dribbble posts received any conversation, and the amount of unique commenters for Dribbble and Behance). For instance, compared to editing, the influence of platform was 4.05 to 9.86 times greater on whether post received any likes and replies and 3.57 to 28.1 times greater on amount of likes and replies received. For physical activity domain, we only saw greater effect size of the level of content diversity on whether a Strava post receive any likes (3.6 times greater) and the amount of likes received on Strava (4.75 times greater), and replies received on Strava and MapMyRun (2.36 and 1.27 times greater).

4.2.1 Having edited text increases response more on dedicated platforms for physical activities, but more on broad-purpose platforms for creativity posts. Our results are mixed for the effect of edited text for responses on platforms with different level of content diversity (*H2-3*). The inclusion of edited text in posts on physical activity posts helps increase the likelihood and amount of responses received (both likes and replies) more on dedicated platforms, as having effect sizes ranging from 1.17 to 1.65 times larger for likelihood of receiving likes and comments, and from 1.07 to 1.2 times larger for amount of responses. We did not find significance in difference on effect size for both likes and replies on MapMyRun. In addition, the inclusion of edited text helps increase the likelihood of having commenters (1.35 times more) and conversation (1.32 times more) on Strava's broad-purpose platform. However, our results also show an opposite trend within the creativity domain - the inclusion of edited text in posts helps increase the likelihood and amount of receiving responses (both likes and replies) more on broad-purpose platforms. Furthermore, we see that including edited text in creativity posts increase the likelihood of having conversation and the amount of commenters more on broad-purpose platforms than dedicated platforms. Our results, as showing compounded effect of increase on different platforms across domains, fail to support our second hypothesis that including edited text would generally increase the scale of response received more on dedicated platforms.

To further interpret the mixed results, we conduct a Log likelihood ratio (LLR) analysis to understand the edited text differences on each platform with different level of content diversity to surface the most distinct word use in text descriptions. As shown in Table 5, the results demonstrate some differences between how activities were described. While text descriptions often consists of words from text templates as mentioned in Table 1, we see more use of words beyond those from text templates on dedicated platforms. For instance, in the physical activity domain, the sharers would describe characteristics about the physical activity they did, such as the weather (*"temp", "cool"*), the activity (*"pace", "time", "route"*), or how it felt (*"felt", "awesome", "good", "easy"*) (e.g., *It is hoooot and sunny! pace was steady, which was awesome since my goal was to not go too fast. I held it to the last mile and was pumped." (Strava)*). Comparingly, we see text on broad-purpose platforms mostly comprised of terms that were from the text templates, such as (*"ran", "km", "workout"*) or the time of day they exercise (*"evening", "morning", "lunchtime"*). This norms of focus on adding additional activity details on dedicated platforms might contribute to the higher increase of response one gets when including edited text to the activity posts on the platform. On dedicated platforms in the creativity domain, conversely, we see people providing technical specifications of what they created (*"cm", "psd", "dpi", "bleed"*), metadata about files (*"file", "download", "attachment"*), and offering business/collaboration opportunities (*"contact", "provide", "available"*) (e.g., *"Hello! I create a 80s-inspired Concept Design, enjoy the video! I am available for projects, contact me if you like my work. Thanks!"*). On broad-purpose platforms, people more commonly edited text to engage in community-centered events (*"daily", "ui", "challenge"*) and ask for support (*"appreciate", "feedback", "please"*) (e.g., *"Day eight of Daily UI challenge! For today, I design a clock app. I was inspired by the design of vintage clock face. As always, any Feedback is appreciated!"*). We suspect the usage of terms that foster engagement could yield more response in the creativity domain, thus given higher increase on social engagement from the edited text on broad-purpose platforms.

Dribbble				Behance				Strava				MapMyRun			
Broad > Dedicated		Dedicated > Broad		Broad > Dedicated		Dedicated > Broad		Broad > Dedicated		Dedicated > Broad		Broad > Dedicated		Dedicated > Broad	
Token	Weight	Token	Weight	Token	Weight	Token	Weight	Token	Weight	Token	Weight	Token	Weight	Token	Weight
shot	0.2467	instagram	-0.6026	full	0.5933	read	-0.8826	lunch	0.0566	mile	-0.7811	ran	0.4395	temp	-0.1716
daily	0.2210	behance	-0.5449	link	0.5145	project	-0.5470	go	0.0558	new	-0.4206	km	0.1536	love	-0.1601
logo	0.2091	twitter	-0.5381	see	0.4974	new	-0.3867	ride	0.0231	time	-0.4124	workout	0.0923	cool	-0.1033
land	0.1933	follow	-0.4642	get	0.4519	work	-0.3798	pax	0.0226	min	-0.4072	detail	0.0808	wind	-0.0939
post	0.1827	facebook	-0.4135	like	0.4356	file	-0.0805	road	0.0151	get	-0.4045	rode	0.0753	route	-0.0891
ui	0.1604	press	-0.4099	appreciate	0.4264	base	-0.0712	log	0.0139	good	-0.4009	morning	0.0568	awesome	-0.0885
app	0.1434	like	-0.3235	look	0.4006	portfolio	-0.0710	meter	0.0104	take	-0.3862	training	0.0427	everyone	-0.0857
page	0.1313	available	-0.3209	please	0.3709	cm	-0.0576	ytd	0.0088	back	-0.3613	work	0.0324	make	-0.0841
dashboard	0.1256	use	-0.2994	late	0.3455	psd	-0.0472	wk	0.0051	felt	-0.3501	early	0.0319	hour	-0.0803
new	0.1141	project	-0.2785	view	0.3316	cmyk	-0.0435	gooch	0.0046	start	-0.3472	walk	0.0287	good	-0.0751
card	0.1113	file	-0.2620	love	0.331	size	-0.0426	runch	0.0044	bit	-0.33	bike	0.0255	life	-0.0731
icon	0.0987	show	-0.2599	case	0.3131	bleed	-0.0426	tweet	0.0038	work	-0.3286	burn	0.0253	go	-0.0703
late	0.0933	hope	-0.2554	post	0.2915	inch	-0.0415	beatdown	0.0036	first	-0.3285	gym	0.0244	humid	-0.0617
wip	0.0871	thanks	-0.2512	hey	0.2765	dpi	-0.0398	thx	0.0031	end	-0.3264	creek	0.0207	well	-0.0595
flyer	0.0867	help	-0.2395	one	0.2718	aim	-0.0385	lunchtime	0.0031	pace	-0.3225	treadmill	0.02	time	-0.0581
concept	0.0844	full	-0.2356	update	0.265	various	-0.0382	lsr	0.003	minute	-0.322	trainer	0.017	wife	-0.0576
check	0.0789	create	-0.2350	guy	0.2643	check	-0.0346	trophy	0.0028	way	-0.3061	climbed	0.0166	boy	-0.0551
checkout	0.0771	buy	-0.2343	last	0.2641	contains	-0.0345	bosley	0.0027	well	-0.3055	tuesday	0.0166	tomorrow	-0.0549
day	0.0737	linkedin	-0.2309	go	0.2621	main	-0.0334	evening	0.0026	stop	-0.3028	october	0.0163	great	-0.0549
onboarding	0.0721	forget	-0.2255	thanks	0.2616	editable	-0.0330	fng	0.0025	right	-0.3001	train	0.0161	felt	-0.0542
letter	0.0706	see	-0.2241	share	0.2596	th	-0.0324	brr	0.0025	last	-0.2978	st	0.0154	happy	-0.0537
redesign	0.0701	contact	-0.2237	finally	0.2546	focus	-0.0309	delivery	0.0023	one	-0.2880	passenger	0.0151	amaze	-0.0528
music	0.0650	download	-0.2177	feedback	0.2504	locate	-0.0283	lida	0.0022	easy	-0.2862	floor	0.0149	guy	-0.0526
template	0.0650	get	-0.2120	study	0.2474	profile	-0.0261	shakeout	0.0021	make	-0.2844	prayer	0.0143	get	-0.0523
animation	0.0649	user	-0.1940	really	0.2386	provide	-0.0254	cheeky	0.0021	leg	-0.2839	r	0.0143	much	-0.0498

Table 5. **Log likelihood Ratio (LLR) for description text from posts with edited text:** The top 25 linguistic tokens with the most positive (left column), and most negative (right column) LLR values across the text descriptions in both platforms from the applications.

4.2.2 Including embedded photos increase the amount of response received on dedicated platform more, but increase the likelihood of receiving responses on broad-purpose platforms more. Similar to results from examining the effects of edited text, we see mixed results for the effect of having embedded photos on effect size on different platform. Our results show that including embedded photos in posts help increase more of the amount of response (both likes, replies, and the amount of unique commenters) for physical activities for around 1.1 times more (except for likes on MapMyRun) on dedicated platforms. However, photos embedded increase the likelihood of receiving any responses more on broad-purpose platforms for all applications (from 1.07 to 2.84 times more). To summarize, our results partially supported our fourth hypothesis (*H2-4*) that effect size is larger on dedicated platforms for the amount of response received, but not the likelihood of receiving response.

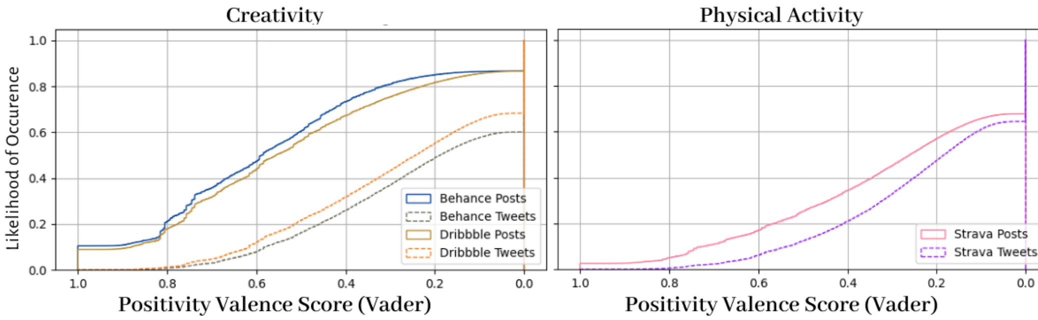


Fig. 5. **Sentiment Analysis Results (for RQ3, *H3-1*)**: The cumulative distribution of the positive sentiment score calculated using VADER on all comment across applications within each domain.

4.3 RQ3: Differences in Text Features of Responses Between Broad-Purpose and Dedicated Platforms

Beyond examining differences in the quantity of responses given on dedicated and broad-purpose social platforms, we seek to understand how people differ in how they write responses to activities shared on each platform. We use textual analysis methods to compare features of the responses to posts in each platform, including sentiment analysis for examining emotional valence, and term frequency-inverse document frequency metric (TF-IDF) along with log likelihood ratios (LLR) for topical relevance.

4.3.1 Sentiment analysis results. To examine tonal differences in typical responses to posts on broad and dedicated platforms, we calculate the sentiment score of each response we collected and aggregated by platform. Figure 5 shows a cumulative distribution function of the positive sentiment score for each comment from the applications, normalized to the number of comments in each application. Overall, we observe that across all applications, the proportion of comments on dedicated platforms that have a positive valence score is larger than the proportion of comments on broad-purpose platforms. We also observe a greater rate of no positive sentiment across the broad-purpose platforms, and larger proportion of full positive valence for the dedicated platforms. In the creativity domain, our results demonstrate that about 20% more comments on dedicated platforms includes positive valence starting from around a valence score of 0.8 and continuing nearly until the comments have no positive valence. To note, the results across the platforms among the Behance and Dribbble aligns closely, suggesting similarity between apps within the same domain. Comments in the physical activity domain shows a relatively smaller difference in proportion, but a similar effect. About 10% more posts to dedicated platforms include higher valence starting from around a valence score of 0.6. The result indicates that dedicated platforms in general have a higher proportion of positive-leaning comments, thus support our first hypothesis (H3-1) that responses on dedicated platforms are more positive in valence comparing to broad-purpose platform. Similar outcomes were shown in the LLR analysis result that positive words were more prevalent on dedicated platforms compared to broad-purpose platforms.

4.3.2 TF-IDF analysis results. We first present the top 25 linguistic tokens sorted by their TF-IDF weights from the three platform pairs across two domains in Table 6. Examining the results, we see similar functional words being used in comments across the applications and domains. These words usually pertain to positive sentiments about the activities being shared (e.g., good, awesome, great, like, love), suggesting similarly commentary styles [81] across the platforms. Additionally, we see

Dribbble				Behance				Strava			
Broad-purpose		Dedicated		Broad-purpose		Dedicated		Broad-purpose		Dedicated	
Token	**Weight**	**Token**	**Weight**	**Token**	**Weight**	**Token**	**Weight**	**Token**	**Weight**	**Token**	**Weight**
thanks	0.0533	love	0.0537	thanks	0.0326	great	0.0500	run	0.0340	thanks	0.0339
work	0.0258	thanks	0.0534	thank	0.0287	thank	0.0487	thanks	0.0262	nice	0.0325
love	0.0257	work	0.0416	work	0.0277	thanks	0.0427	good	0.0241	good	0.0315
look	0.0230	great	0.0385	love	0.0217	love	0.0415	great	0.0211	run	0.0283
like	0.0215	awesome	0.0345	look	0.0174	awesome	0.0385	nice	0.0180	great	0.0267
thank	0.0203	thank	0.0330	like	0.0173	good	0.0306	time	0.0175	ride	0.0257
nice	0.0183	cool	0.0298	great	0.0147	amaze	0.0289	like	0.0164	time	0.0174
share	0.0182	like	0.0250	good	0.0145	really	0.0281	ride	0.0153	look	0.0170
great	0.0166	good	0.0244	nice	0.0136	cool	0.0266	look	0.0152	mate	0.0159
design	0.0162	look	0.0243	make	0.0132	beautiful	0.0259	work	0.0147	like	0.0149
good	0.0155	really	0.0218	really	0.0121	like	0.0245	day	0.0147	day	0.0130
make	0.0152	color	0.0173	design	0.0120	project	0.0221	mile	0.0141	mile	0.0124
use	0.0141	shot	0.0158	amaze	0.0107	job	0.0211	way	0.0128	awesome	0.0122
awesome	0.0140	welcome	0.0149	awesome	0.0099	wow	0.0201	thank	0.0125	work	0.0121
really	0.0126	beautiful	0.0137	project	0.0096	check	0.0196	think	0.0109	today	0.0121
think	0.0103	clean	0.0136	use	0.0092	design	0.0170	today	0.0102	lol	0.0120
dribbble	0.0092	wow	0.0134	appreciate	0.0086	look	0.0162	bike	0.0100	way	0.0102
cool	0.0090	design	0.0133	check	0.0079	appreciate	0.0118	need	0.0096	cheer	0.0102
know	0.0089	amaze	0.0131	cool	0.0076	color	0.0092	mate	0.0096	bike	0.0101
time	0.0082	job	0.0104	bro	0.0075	time	0.0079	awesome	0.0095	pace	0.0099
need	0.0081	style	0.0101	think	0.0071	clean	0.0067	know	0.0095	think	0.0093
try	0.0076	use	0.0099	need	0.0071	lot	0.0066	week	0.0094	yes	0.0088
yeah	0.0072	make	0.0092	know	0.0069	style	0.0063	year	0.0094	wow	0.0086
right	0.0069	illustration	0.0079	time	0.0068	feedback	0.0062	make	0.0090	week	0.0084
haha	0.0069	animation	0.0078	dm	0.0066	presentation	0.0062	love	0.0085	love	0.0082

Table 6. **TF-IDF results (for RQ3, H3-2)**: The top 25 most frequent linguistic tokens and their weights in comments on each platform across applications in descending order.

the use of words such as "thank/thanks" and "appreciate" in the list which suggest the appearance of reciprocal exchange and conversation in the replies. Our analysis also surface domain-specific words that exclusively appear within the two domains. These terms are often used along with discussing or referring to the activity of the domain. For instance, terms including "run", "ride", "mile", "time" occur frequently in the physical activity domain and "share", "design", "color", "style", "beautiful" all occur frequently in the creativity domain. Within domains, there were also terms that are mentioned exclusively on a specific application, such as "illustration", "animation", "icon" on Dribbble. This suggests that the applications might also have slightly different topical foci within the same larger domain of creative works.

4.3.3 LLR analysis results. Table 7 shows the result from our LLR analysis comparing terms which occurred more frequently for more dedicated or more broad platforms across the two domains. Across the domains, we see that many words that are more frequent on dedicated platforms are supportive or encouraging words (e.g., awesome, nice, great, impressive, excellent). For instance, the audience often leave complimentary or encouraging comments to the sharer. Examples include: *"Awesome pace and mileage baby! x" (Strava), "great work my friend!! style is nice n cool .." (Behance)* [2] This trend aligns with the result of our sentiment analysis that across all applications (Strava, Behance, Dribbble), there are higher proportion of positive words used on dedicated platforms comparing to broad-purpose platforms.

Within physical activity, we further observe that some terms more frequently used on dedicated platforms describe activity-specific accomplishments, such as "pr" (personal record), "speed", and "pace". When comments center around these activities, people often provide activity-specific

[2]To preserve anonymity of the sharers in our dataset, all comments quoted in the results were slightly tweaked to ensure them being not searchable.

Dribbble				Behance				Strava			
Broad>Dedicated		Dedicated>Broad		Broad>Dedicated		Dedicated>Broad		Broad>Dedicated		Dedicated>Broad	
Token	**Weight**	**Token**	**Weight**	**Token**	**Weight**	**Token**	**Weight**	**Token**	**Weight**	**Token**	**Weight**
share	0.3731	nice	-0.3968	make	0.5834	nice	-0.1140	#uponeaglewings	0.0940	nice	-0.2809
get	0.2756	welcome	-0.3304	one	0.5667	job	-0.0613	please	0.0919	ride	-0.2748
need	0.2184	clean	-0.3014	get	0.5567	please	-0.0593	strava	0.0892	mate	-0.2433
know	0.2027	color	-0.2998	look	0.4487	excellent	-0.0583	tweet	0.0867	lol	-0.2403
make	0.1751	cool	-0.2849	see	0.4382	advance	-0.0510	walk	0.0828	cheer	-0.1912
would	0.1745	awesome	-0.2530	use	0.4180	presentation	-0.0497	use	0.0783	thanks	-0.1904
go	0.1743	great	-0.2525	go	0.4166	valuable	-0.0493	#sparkysrunningclub	0.0771	good	-0.1818
yeah	0.1687	love	-0.2487	dm	0.4110	beautiful	-0.0341	link	0.0745	great	-0.1727
try	0.1683	shot	-0.2343	know	0.4109	wow	-0.0301	#earthathon	0.0743	pace	-0.1649
sure	0.1654	illustration	-0.2188	need	0.4089	impressive	-0.0283	min	0.0731	wind	-0.1571
link	0.1639	beautiful	-0.2136	think	0.3855	checkout	-0.0253	data	0.0718	pic	-0.1534
something	0.1616	style	-0.2025	thanks	0.3699	superb	-0.0200	km	0.0690	guy	-0.1439
think	0.1578	wow	-0.1936	come	0.3545	visit	-0.0188	app	0.0679	well	-0.139
time	0.1572	job	-0.1830	still	0.3458	combination	-0.0187	support	0.0672	climb	-0.1390
please	0.1560	instagram	-0.1669	thing	0.3437	greatly	-0.0180	#ukrunchat	0.0610	wow	-0.1390
day	0.1547	lovely	-0.1568	behance	0.3263	feedback	-0.0171	check	0.0554	see	-0.1310
still	0.1535	really	-0.1399	logo	0.3238	appreciation	-0.0152	#strava	0.0553	effort	-0.1290
app	0.1522	amaze	-0.1387	much	0.3237	elegant	-0.0149	w/kg	0.0550	look	-0.1241
thing	0.1518	behance	-0.1343	year	0.3192	awesome	-0.0137	share	0.0520	today	-0.1234
tweet	0.1463	cute	-0.1315	stuff	0.3130	stylish	-0.0129	activity	0.0503	awesome	-0.1229
invite	0.1456	guy	-0.1272	would	0.3122	wooow	-0.0119	help	0.0493	pr	-0.1142
#dailyui	0.1449	facebook	-0.1229	try	0.3099	excelent	-0.0118	thank	0.0473	speed	-0.1084
post	0.1387	work	-0.1225	say	0.3094	coool	-0.0114	team	0.0455	tough	-0.1029
use	0.1386	texture	-0.1109	like	0.3067	nicely	-0.0113	gps	0.0453	strong	-0.1013
help	0.1357	nicely	-0.1023	day	0.2999	composition	-0.0111	city	0.0442	photo	-0.0989

Table 7. **Log likelihood ratio (LLR) results (for RQ3, H3-2)**: The top 25 linguistic tokens with the most positive (left column), and most negative (right column) LLR values across the comments in both platforms from the application. There are terms that are specifically used within the app, such as *"w/kg"* (watts/kilogram) and *"pr"* (personal record) on Strava.

encouragements (e.g., *"Great workout man! good pace!" (Strava), "much fast very speed" (Strava)*) or further having comments that are more in-depth about details of the activity (e.g., *"Well done! I'm very impressed you can do this at the same pace as 10km. putting more effort into the shorter runs and you may surprise yourself!" (Strava), "You could try half sessions of hills then speed up on the flat. 3 to 4 min half mile intervals, with 1 min rest" (Strava)*). Words describing the effort of undertaking the activity are similarly more common in comments on dedicated platforms ("tough", "effort"), as they often contains support towards the sharer when disclosing challenges they experienced (e.g., *"the elevation sure looks tough. you did well when I've been lazy this weekend!" (Strava), "Great effort [redacted]! - keep it up! Almost ready for the half marathon" (Strava)*). For creativity domain, words focusing on specific visual aspects of the shared activity are more prevalent on dedicated platforms than on broad-purpose platforms. For instance, terms such as "color", "illustration", "texture", "layout", and "style" are all used more commonly in posts to Dribbble's dedicated platform than to its broad-purpose platform. Within Behance, similar terms including "presentation", "composition", and "combination" are used more commonly on its dedicated platform. Similar to general trends on dedicated platforms, these terms are used for complimenting aspects of activities specifically (e.g., *"love this shot so so much!! you master the colors and contrast!" (Dribbble), "Love your combination of design and concept, so clean and unique with impressive presentation!" (Behance)*), or sometimes dive deeper in detailed discussions (e.g., *"Love that you combine the colors. The execution of Fonts are super cool! I think you can use some more mockup or presentation for make it more appealing. Overall super impressive work! Mind-blowing!!" (Behance), "super clean and neat work as usual my friend. The illustrations works well for representing what you're communicating in each card visually. some motion to this would be fantastic!! Also, is the step 2 the last step in this process, or is there more that* *comes after this?" (Dribbble), "Awesome work! I was thinking if the shadows come from one of the main color, that box at the front should have some blue-ish shadow other than pink." (Dribbble)*).

Conversely, on broad-purpose platforms, we see more terms describing the kind of activity completed in the physical activity domain. Example terms including ones used to describe the type of activity people do ("walk") and units pertaining to how much of an activity someone might do ("min", "km", "w/kg"). In these cases, commenters are often providing encouragement or feedback on tracked data, which often focus on the sharer's performance (e.g., *"@[redacted] That's a looong walk you did! nice job!" (Strava), "@[redacted] @[redacted] just 5.1 w/kg? wow. that's impressive after active for the first 150km of the race." (Strava)*). Across domains, we frequently see more comments on broad-purpose platforms that contain hashtags (#dailyui, #uponeaglewings, #ukrunchat), describing the act of sharing ("link", "dm"), or words pertaining to one of the platforms themselves ("tweet", "strava", "dribbble", "behance"). These hashtags are mostly used for events or shared between users that identifies as member of a specific subcommunity. For instance, "#dailyui" is a design challenge on Dribbble that encourages people to share their UI design work everyday. Comments often includes discussion about the work, or original poster sequentially sharing their daily logs. (e.g., *"@[redacted] @dribbble Welcome aboard to the new challenges of #dailyui!" (Dribbble), "@[redacted] Appreciate it [redacted]! I will sketch out some in detail, but I do this #dailyUI challenge mostly as quick exercises" (Dribbble)*). *#earthathon* and *#ukrunchat* were used amongst members of each physical activity groups that often were general encouragements. (e.g., *"@[redacted] looks like the perfect weather for you Tim! Way to run these hills for #uponeaglewings #earthathon " (Strava), "@[redacted] That's what i'm saying! You're almost a #ukrunchat favorite now!" (Strava)*).

We interpret these differences as dedicated platforms often have greater focus on the activities themselves, whereas broad-purpose platforms have more focus on the sociality around the activity. For dedicated platforms, we see a general trend of audiences providing positive and encouraging comments towards the sharer, while oftentimes showing support to the sharer when they disclose challenging experiences. To summarize, our results partially supported our second hypothesis (*H3-2*). Through our LLR analysis, we saw greater usage of words describing activity-specific details, accomplishments, and efforts across both domains on dedicated platforms, which we interpret as having higher topical relevance among comments on dedicated platforms. However, comments on broad-purpose platforms tended to use more relevant hashtags, which could be interpreted as focus on sociality, and therefore relevant to the goal of sharing activities. Along with the sentiment analysis results, this also supports our first hypothesis (*H3-1*) that responses on dedicated platforms are more positive in valence comparing to broad-purpose platform. In the case of broad-purpose platforms, we highlight how people often leverage the different mechanisms that they provide in order to connect or communicate with others, such as encourage switching to private communication channels through *"dm"*) or use hashtags (e.g., *#dailyui* on Dribbble, or *#uponeaglewings*, *#sparkysrunningclub*, *#earthathon*, *#ukrunchat* on Strava) to foster a smaller community within a broad-purpose platform. These differences also align with how activity sharers includes text descriptions differently between the platforms, as described in 4.2. For instance, sharing physical activity on dedicated platforms often contains more details through the inclusion of tracked data and feeling, and sharing on broad-purpose platforms in creativity domain often includes terms that encourage social engagement (e.g., "appreciate", "feedback", "please", "dailyui").

5 Discussion

5.1 Summary of Findings

Our study suggested that sharing activity through dedicated platforms yield more social engagement in quantity compared to sharing on broad-purpose platforms. We found statistical significance

Research Question	Hypothesis	Main Takeaway
RQ1: How does a platform's level of content diversity influence the **quantity of response** people receive when sharing their activity?	**1-1.** Posts on *dedicated platforms* will be more likely and receive more response than than their counterparts to *broad-purpose platforms.*	**Supported**. Sharing activity on dedicated platform resulted in higher likelihood (except MapMyRun) and more responses (for all apps) compared to broad-purpose platform, ranging from 1.38 to 149.22 times more likes, 1.35 to 18.67 times more replies, 1.1 to 1.69 times more commenters, and 3.32 to 11.96 times more likely to have conversation.
RQ2: How does use of **editing features** in activity sharing posts influence the quantity of response that people receive across the platforms?	**2-1. Using editing features** results in higher likelihood in receiving response as well as more responses.	**Supported**. Activity posts that used editing features were more likely, and received more responses on all platforms (except for embedded photo on unique commenter amount on Strava).
	2-2. Response amount is influenced more strongly by a platform's **level of content diversity** than the **use of editing features**.	**Partially supported**. Effect size of platform's level of content diversity were greater than using editing features for likelihood of receiving and amount of likes (3.61 to 28.10 times more) and replies (1.13 to 7.84 times more) in the creativity domain, but generally less than using editing features for likelihood of receiving and amount of response in physical activity domain.
	2-3. Use of editing features to change text increases response amount more on *dedicated platforms* than on *broad-purpose platforms.*	**Partially supported**. Including edited text increased the likelihood of receiving response more (1.17 to 1.65 times more on likes and comments) and amount of response (1.07 to 1.22 times more on likes and comments for Strava) on dedicated platforms for physical activities. However, it increased both the likelihood and amount of receiving responses more on broad-purpose platforms in the creativity domain (1.50 to 3.44 times more).
	2-4. Use of editing features to embed photos increases response amount more on *dedicated platforms* than on *broad-purpose platforms.*	**Partially supported**. Including embedded photos in activity sharing resulted in slightly more increase of response received on dedicated platforms (1.05 to 1.11 times more), but increase the likelihood of receiving any response more on broad-purpose platforms (1.24 to 2.84 times more) in the physical activity domain.
RQ3: How does the **textual features of response** differ between broad-purpose and dedicated platforms?	**3-1.** Activity posts to *dedicated platforms* will receive more response in positive valence than their counterparts on *broad-purpose platforms.*	**Supported**. Comments received on dedicated platforms were generally more positive in valence, which showed more supportive words use (e.g., awesome, cute, great, impressive, excellent), than on broad-purpose platform.
	3-2. Activity posts to *dedicated platforms* will have more topical relevance than their counterparts on *broad-purpose platforms.*	**Partially supported**. Comments received on dedicated platforms generally mentioned more activity-specific details (e.g., "pr" (personal record), pace; color, texture), but comments received on broad-purpose platform tended to include more relevant hashtags.

Table 8. Summary of responses to our research questions and hypotheses, some of which were supported and others partially supported by our analysis.

among four variables regarding the response, ranging from 1.38 to 149.22 times more likes, 1.35 to 18.67 times more replies, 1.1 to 1.69 times more commenters, and 3.57 to 11.96 times more likely to have conversation, depending on the platform. In addition to platform difference, we further identify an effect of embedding edited content, including photos or text, on the sharing response in platforms with different level of content diversity.

While our results aligned with previous work on demonstrating that using editing features to embed photos or edit texts when sharing activities would garner more response [29], we saw that the effect was generally larger in scale on broad-purpose platforms compared to dedicated platforms. More specifically, including embedded photos in activity sharing resulted in greater increase in response on broad-purpose compared to dedicated platforms, resulting in a 10-30% increase in likelihood that a post receives likes, receiving twice as many likes on average.

Additionally, our examination of text features in responses showed that comments received on dedicated platforms possess more positivity, as more encouraging words were used. Further, people commenting on dedicated platforms tended to refer to specific details of the activities as shown by the amount of activity-specific terms. In contrast, comments to broad-purpose platforms tended to focus more on the sociality surrounding the activity, including words pertaining to the act of sharing or specific platforms.

5.2 How engagement differs between broad-purpose and dedicated platforms

Based on our findings, we believe that people generally achieve more desirable sharing outcomes on dedicated platforms compared to broad-purpose platforms. The overwhelmingly larger quantity in response on dedicated platforms indicated in our results suggests that sharing activity on dedicated platforms were ostensibly the desired sharing space for individuals who were aiming to maximize the quantity of response. Given that people often have a larger and more diverse set of audiences on broad-purpose platforms, these findings further emphasize the utility of dedicated platforms in gathering more response for the sharer. Past literature in social computing discuss the conception of "imagined audience" [64] from social media user, and suggested that people try to look for the largest quantity of the desired audience when sharing or posting online [99, 112]. Our work therefore contributes an understanding on platform selection that could help sharers in optimizing the outcome of sharing activities.

On top of confirming the effect of the use of editing features helping to increase the quantity of sharing outcome, our findings also reveal that using editing features could impact sharing response differently based on the platform's level of content diversity. We suspect that the reason for such difference resulted from how platforms focusing on specific activities facilitate norms around sharing. On dedicated platforms, we suspect the sharing goal and intent is largely implicit and well-understood by the audience. The existence of a dedicated platform and frequent contributions to it already suggests that people have a collective understanding around why someone might be sharing their activity on it, and what they might want in return. Conversely, activities shared on broad-purpose platforms may lack such context given their diverse purpose and usage collapse. Sharers thus have to proactively fill in information or details to complement this loss of context, and can be rewarded with better sharing outcomes when they do. Though, we still find that such benefit is relatively low compared to sharing with a dedicated audience.

Digging deeper into the use of editing features, our results also show that the interaction between platform type and type of content added using editing features influenced the effect size of response. Including edited text in the physical activity domain increases the likelihood and amount of response more on dedicated platforms, while for creativity domain it increases the likelihood and amount of response more on broad-purpose platforms. Conversely, including embedded photos on physical activity platforms increases the likelihood of response more on broad-purpose platforms and the amount of response more on dedicated platforms. We believe such differences were the result of an interplay between the influence of the type of content added using editing features, domain, and platform's level of content diversity. For instance, the effect of embedding edited text was greater on dedicated platforms for physical activity as it help bridging the gap on sharing intent as the sharing often centers tracked data (e.g., distance ran, pace). Including photos when sharing physical activity posts on broad-purpose platforms could help attract the audience's attention, since contents shared on these platforms were often diverse in topics and intentions. On the other hand, people sharing in the creativity domain on dedicated platforms often have more specific and well-understood goals in mind, such as seeking critique [46, 108], or professional development [62]. Therefore, embedding edited text when sharing on broad-purpose platforms in the creativity domains might provide additional, stronger shared understanding as context thus leads to greater effect size.

5.3 Design Recommendations

We offer recommendations for the design of social platforms for activity sharing as well as for activity tracking applications which support cross-posting to multiple platforms.

5.3.1 Recommendations for Platform Design. Our findings demonstrated how sharing on broad-purpose and dedicated platforms could influence the level and kind of response people receive when sharing. While the results helped theorize how each platform may help achieving sharing goals, which may lead to individual users making better activity sharing decisions online, here we also point out several design recommendations which could be incorporated into platform design that might lead to improved sharing outcomes for platform users.

Our findings suggest that sharing activity on dedicated platforms, for the most part, result in better social engagement comparing to sharing on broad-purpose platforms. This result largely implies that when designing future activity sharing apps, either for commercial or research purposes, supporting sharing on a dedicated platform can be helpful for achieving better social outcomes. Nevertheless, to achieve such a design, designers needs to consider how to build an effective dedicated community where members possess interest in engaging. Past work has acknowledged the challenge of building and maintaining dedicated online communities [46]. Further, bootstrapping an audience on a broad-purpose platform first can demonstrate that there is significant interest in activity sharing before considering investing in creating dedicated features [31]. One interpretation for the slow decline of cross-posted activities in our dataset over time (Fig. 4 from Methods) is that applications and their users first sought to achieve social support externally, but once the dedicated social platforms reached critical mass, they were able to achieve their desired social benefits without the broad-purpose platforms. To exploit the benefit of dedicated platforms, we recommend designers of future sharing platforms consider effective ways of accumulating or recruiting members to the dedicated community that would enable sharers on the platforms to receive desirable sharing outcomes.

Activity sharers might have different sharing goals in mind, such as seeking constructive feedback, holding themselves accountable, or informing or motivating others. Selecting the right channel for sharing to reach the desired audience for sharing has been largely discussed in the past [76, 94]. As our work showcased that sharing on different platforms could result in different quantity of response, we propose that designs that help guide individuals to make decisions on whether to share on broad-purpose, dedicated platforms, or both could be incorporated into current social platforms, which could help the sharer achieve their goal of reaching a desired audience. For instance, designs could incorporate guidance on platform selection when individuals editing content when sharing. When people are sharing with the aim to reach a larger amount of audience, but where response is not as crucial, they could be directed to posting on one's broad-purpose platforms. Conversely, when aiming to reach for a higher rate of social engagement, it could be suggested that dedicated platforms might be a good destination for sharing. A challenge in this space is that sharing decisions are often not explicit on dedicated applications, such as occurring whenever someone uses a dedicated application to log or track their activity. But, explicit encouragement to cross-post could help, such as around major activities or accomplishments which might be of interest to a large audience. Past work has also demonstrated how individual characteristics [65] and motivations [59] could contribute to making decisions on selecting from different platforms. Another strategy that might help individuals make decisions on where to share is simply making people aware of the different response typically received across different platforms. In doing so, design choices such as visualization and coordinated views that aggregates responses from different sources [107], or automating suggestions to cross-post based on similar sharer motivation and desired response type [99] might also be beneficial in reaching specific sharing goals such as seeking constructive feedback or initiating conversation. Providing sharers with opportunities to be aware of and reflect on sharing motivation, or bring attention to differences in typical sharing outcomes of platforms, could help navigating how platform selection could support the sharer to reach their desired sharing goal.

5.3.2 Recommendations for Cross-Posting Design. While our findings highlighted the differences in sharing the same activity on broad-purpose and dedicated platforms, they also point to potential in expanding mechanisms around selective sharing within platforms with different level of content diversity based on the different responses that were received on them. Past work has also demonstrated that platforms that focused on similar activity might provide different responses or kinds of support [16, 108], supporting the idea that elaborating more about the activity being shared to different platforms might help with reaching desired sharing outcomes. Given the diverse goals that people might have with sharing, we propose that multiple templates or guidance tailored to different sharing goals could be incorporated into the design of dedicated and broad-purpose platforms. For instance, as we saw more use of positive and encouraging words on dedicated platforms, templates that encourage reflection on how one overcame difficulties in their activities, or self-disclosure of negative experiences might help sharers on dedicated platforms leverage this encouragement to receive greater emotional support. Broad-purpose platforms, on the other hand, could provide guidance or templates which encourage sharing of different level of details about the activity, as audiences often provide comments about the practical details about the activity. Past work has demonstrated mechanisms to sharing different information about activities, such as sharing at different levels of detail for different audiences [26, 82] or highlighting progress made since previous times shared [28, 46]. Our work furthers these suggestions by suggesting that there is benefit to tailoring guidance to the norms of the platforms, both by adding evidence or information frequently needed on a platform to better interpret activities, as well as to leverage the kinds of support the platform is effective as providing.

Our findings also point out that embedding edited content, including photos and text, boost response received on broad-purpose platforms more than on dedicated platforms. While previous work has highlighted the increase in response when shared activities include content through using editing features [29], we suspect that such differences between the platforms derive from how broad-purpose platforms are currently supporting editing when sharing activities. Broad-purpose platforms, given their general goal of supporting sharing and social interaction while covering a broad range of sharing content, are understandably less likely to incorporate features that encourage or support guidance around editing, instead aiming to provide a blank enough canvas for users to appropriate the social features towards their goals. To achieve the benefit from embedding edited content, we recommend that dedicated platforms could geared its feature to cross-post activity on broad-purpose platform with features such as guidance, prompts, or templates that were already incorporated in sharing on dedicated platforms to help individuals in getting better sharing outcome on broad-purpose platforms. For instance, incorporating guidance design for writing to request for feedback on creative work [19] or storytelling templates that help highlight progress or accomplishments in activity [28] could potentially be helpful in supporting edits. We also highlight the importance of encouraging edits to subsequently encourage a better platform norm for social engagement. From our findings, we saw a large dropoff in inclusion of images when moving from dedicated to broad platforms for most of the apps. While embedding images might not be as impactful on broad-purpose platforms as a factor for generating responses in dedicated platforms, encouraging the embedding of such content, whether before (e.g., whenever you make a post but before deciding to share it) or during sharing (e.g., when you export it), can help improve the outcomes of sharing on board-purpose platforms.

5.4 Limitations and Future Work

Beyond the content itself, response rate to posts is largely influenced by aspects about how people use platforms, such as the amount of followers a person have on the app and how often they post. Nevertheless, when performing analysis, we did not account for these aspects for several reasons. First, we were limited in accessing information about accounts, including followers on many of the platforms and frequency or content other posts made by the user. Second, follower count and posting behavior for each account could change over time. It is likely that a person's earlier posts had fewer followers compared to their more recent posts, and that a person's post frequency is inconsistent over their account's lifespan. Third, the effect of follower counts might diminish since all posts were public within the platforms we chose. Therefore, ostensibly the accounts that could engage with the posts could be anyone, instead of only accounts who follow the account posting. Finally, we selected dedicated platforms that have highly similar social engagement features to our broad-purpose platform to minimize the influence on specific design choices for social engagement. While the dedicated platforms provided similar editing features, social awareness streams, comments in text, and one-click responses, other subtle differences between the platforms may influence the response. Further analyses which are able to control for these factors could provide insight into the relative effect of audience size and frequency of posting versus a platform's content diversity.

Applications constantly make updates to features and policy changes across time. Platform features were not static, and could lead to deviation of posts attributions we observed on the platform. For instance, some platforms currently require embedding at least one image to activity sharing posts, but we saw posts we collected from an earlier time period containing no photos embedded. However, we acknowledge that the guidance provided by these edit-supporting features might change over time. Activities collected in our dataset, therefore, could have been generated through multiple versions with different editing features, with different guidance and requirements. We address this issue through conducting bottom-up examination of collected data, such as identifying text patterns of activity description based on similarity within a large quantity of posts, and highlight significant differences of image being present between platforms which proved version difference of image requirements to be agnostic towards the results differences.

By looking only at activities which were cross-posted, our analysis represents a small subset of activities that people share on the dedicated platforms. We do not know for certain whether the activities which were cross-posted are more or less likely to garner responses or include certain linguistic features. In terms of response, there are reasons to think that cross-posted activities have both more and fewer responses than the typical activity on dedicated platforms. On one hand, cross-posted activities are more likely to be from people who are deeply motivated by social engagement, as evidenced by their desire to seek out engagement from more than one platform, suggesting that they have a robust social network on the dedicated platform. On the other hand, they may have cross-posted to a broader social network because they sought a larger audience than they have on the dedicated platform, suggesting that they would receive relatively little response on the dedicated platform. Overall, further work is needed to understand why people might cross-post activities, and what they hope to get out of each audience.

We note some limitations of using Twitter as a dedicated platform of choice. Responses may be different, or higher in quantity, on other broad-purpose platforms. For example, Instagram centers image content, which might be more beneficial towards eliciting response around activity-sharing. Other broad-purpose networks which center particular types of social relationships (e.g., “friends” on Facebook) may also elicit greater or different levels of response, which warrants deeper examination. Further, recent changes in perceptions and use of Twitter, which occurred after we completed collecting our dataset, may further change people’s practices around the platform. Technical limitations led us to select Twitter, but some care should be taken in generalizing our results to other platforms. We also acknowledge that our data was collected prior to major API changes to Twitter and other social platforms.

While we sought out variety in the dedicated platforms we selected for analysis, there is opportunity to further our understanding around the influence of a platform’s content diversity on response by examining other platforms and other activity domains. For instance, people sharing domains that are often considered more personal (e.g., food) likely receive more or qualitatively different response on dedicated communities around the activity of eating and dieting [21, 53] instead of broad-purpose social media [21, 30]. In domains like learning, there may be stronger affinities present like a shared school affiliation, which might result in even greater response on dedicated platforms where that identity is shared than broad-purpose platforms. Additionally, a person’s goal for sharing an activity might change how activities are represented, and thus change what and how response is received by platforms. When sharing activities related to studying, past work suggests that accountability is a common motivation [85], which may not require as much domain-specific understanding to support. Further work investigating activities shared towards specific goals such as accountability can further elaborate on the influence of content diversity on response.

We note that the results from using VADER to analyze emotional valence could be subjective to influence from differences in posting style or other factors. For instance, when users respond with longer comments, the positivity scores could be balanced out with more negative content. Beyond positivity and negativity, further work could take a deeper look into additional dimensions of textual response differences across platforms, such as trying to categorize developed platform norms.

Beyond quantity and quality of engagement, understanding the temporality of engagement (e.g., when do audiences leave likes and comments) could help contribute understanding of how communities use platforms with varied diversity. For example, it may be that audiences engage with activity posts to dedicated platforms for longer periods of time, which may contribute to our depth of discussion. Platform limitations only enabled us to capture timing of comments for Twitter, where we observed that 80% to 92% of posts were engaged with only within the first two days after posting, depending on the activity (Strava being highest, Behance being lowest). We see value in examining temporality differences among platforms where that information is readily available.

6 Conclusion

In comparing the responses that people receive when sharing activities on both dedicated and broad-purpose social platforms, we find that the quantity of response is typically higher on dedicated platforms in spite of their smaller audience reach. However, using editing features to include content like edited text and images have greater positive influence in response on broad-purpose platforms. We further find that people tend to include more comments referencing qualities surrounding the effort which went into the activities, as well as include more positive and encouraging words. Overall, these findings suggest that people trade off the benefit of sheer audience reach on broad-purpose platforms with the likelihood of engagement on dedicated platforms. We suggest that sharing features aim to align with the respective norms of each platform, more explicitly articulating the sharing goal for a broad-purpose audience while posing more specific questions or requests to dedicated audiences.

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References

[1] 2022. Twitter API for Academic Research | Products | Twitter Developer Platform. https://developer.twitter.com/en/products/twitter-api/academic-research. Accessed: 2022-08-31.

[2] 2023. Hearts on Twitter. blog.twitter.com/en_us/a/2015/hearts-on-twitter. Accessed: 2023-04-01.

[3] 2023. Reminder to migrate to the new Free, Basic, or Enterprise plans of the Twitter API - Announcements - Twitter Developers. https://twittercommunity.com/t/reminder-to-migrate-to-the-new-free-basic-or-enterprise-plans-of-the-twitter-api/189737. Accessed: 2023-04-01.

[4] Nazanin Andalibi, Oliver L. Haimson, Munmun De Choudhury, and Andrea Forte. 2018. Social Support, Reciprocity, and Anonymity in Responses to Sexual Abuse Disclosures on Social Media. *ACM Trans. Comput.-Hum. Interact.* 25, 5, Article 28 (oct 2018), 35 pages. https://doi.org/10.1145/3234942

[5] Nazanin Andalibi, Pinar Ozturk, and Andrea Forte. 2017. Sensitive Self-Disclosures, Responses, and Social Support on Instagram: The Case of Depression. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing* (Portland, Oregon, USA) *(CSCW '17)*. Association for Computing Machinery, New York, NY, USA, 1485–1500. https://doi.org/10.1145/2998181.2998243

[6] Jaime Arguello, Brian S. Butler, Elisabeth Joyce, Robert Kraut, Kimberly S. Ling, Carolyn Rosé, and Xiaoqing Wang. 2006. Talk to Me: Foundations for Successful Individual-Group Interactions in Online Communities. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Montréal, Québec, Canada) *(CHI '06)*. Association for Computing Machinery, New York, NY, USA, 959–968. https://doi.org/10.1145/1124772.1124916

[7] Eric P.S. Baumer, Sherri Jean Katz, Jill E. Freeman, Phil Adams, Amy L. Gonzales, John Pollak, Daniela Retelny, Jeff Niederdeppe, Christine M. Olson, and Geri K. Gay. 2012. Prescriptive Persuasion and Open-Ended Social Awareness: Expanding the Design Space of Mobile Health. In *Proceedings of the ACM 2012 Conference on Computer Supported Cooperative Work* (Seattle, Washington, USA) *(CSCW '12)*. Association for Computing Machinery, New York, NY, USA, 475–484. https://doi.org/10.1145/2145204.2145279

[8] Michael S. Bernstein, Adam Marcus, David R. Karger, and Robert C. Miller. 2010. Enhancing directed content sharing on the web. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Atlanta, Georgia, USA) *(CHI '10)*. Association for Computing Machinery, New York, NY, USA, 971–980. https://doi.org/10.1145/1753326.1753470

[9] danah m. boyd and Nicole B. Ellison. 2007. Social Network Sites: Definition, History, and Scholarship. *Journal of Computer-Mediated Communication* 13, 1 (2007), 210–230. https://doi.org/10.1111/j.1083-6101.2007.00393.x arXiv:https://onlinelibrary.wiley.com/doi/pdf/10.1111/j.1083-6101.2007.00393.x

[10] Moira Burke and Mike Develin. 2016. Once More with Feeling: Supportive Responses to Social Sharing on Facebook. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing* (San Francisco, California, USA) *(CSCW '16)*. Association for Computing Machinery, New York, NY, USA, 1462–1474. https://doi.org/10.1145/2818048.2835199

[11] Moira Burke and Robert E. Kraut. 2014. Growing Closer on Facebook: Changes in Tie Strength through Social Network Site Use. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI '14)*. Association for Computing Machinery, New York, NY, USA, 4187–4196. https://doi.org/10.1145/2556288.2557094

[12] Moira Burke and Robert E. Kraut. 2016. The Relationship Between Facebook Use and Well-Being Depends on Communication Type and Tie Strength. *Journal of Computer-Mediated Communication* 21, 4 (05 2016), 265–281. https:

//doi.org/10.1111/jcc4.12162 arXiv:https://academic.oup.com/jcmc/article-pdf/21/4/265/22316334/jjcmcom0265.pdf
[13] Moira Burke, Cameron Marlow, and Thomas Lento. 2009. Feed Me: Motivating Newcomer Contribution in Social Network Sites. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Boston, MA, USA) *(CHI '09)*. Association for Computing Machinery, New York, NY, USA, 945–954. https://doi.org/10.1145/1518701.1518847
[14] Brian S. Butler and Xiaoqing Wang. 2012. The Cross-Purposes of Cross-Posting: Boundary Reshaping Behavior in Online Discussion Communities. *Information Systems Research* 23, 3-part-2 (2012), 993–1010. https://doi.org/10.1287/isre.1110.0378 arXiv:https://doi.org/10.1287/isre.1110.0378
[15] Julie Campbell, Cecilia Aragon, Katie Davis, Sarah Evans, Abigail Evans, and David Randall. 2016. Thousands of Positive Reviews: Distributed Mentoring in Online Fan Communities. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing* (San Francisco, California, USA) *(CSCW '16)*. Association for Computing Machinery, New York, NY, USA, 691–704. https://doi.org/10.1145/2818048.2819934
[16] Stevie Chancellor, Andrea Hu, and Munmun De Choudhury. 2018. Norms Matter: Contrasting Social Support Around Behavior Change in Online Weight Loss Communities. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–14. https://doi.org/10.1145/3173574.3174240
[17] Diane D. Chapman, Julia Storberg-Walker, and Sophia J. Stone. 2008. Hitting Reply: A Qualitative Study to Understand Student Decisions to Respond to Online Discussion Postings. *E-Learning and Digital Media* 5, 1 (2008), 29–39. https://doi.org/10.2304/elea.2008.5.1.29 arXiv:https://doi.org/10.2304/elea.2008.5.1.29
[18] Yixin Chen and Yang Xu. 2021. Social Support is Contagious: Exploring the Effect of Social Support in Online Mental Health Communities. In *Extended Abstracts of the 2021 CHI Conference on Human Factors in Computing Systems* (<conf-loc>, <city>Yokohama</city>, <country>Japan</country>, </conf-loc>) *(CHI EA '21)*. Association for Computing Machinery, New York, NY, USA, Article 286, 6 pages. https://doi.org/10.1145/3411763.3451644
[19] Ruijia Cheng, Ziwen Zeng, Maysnow Liu, and Steven Dow. 2020. Critique Me: Exploring How Creators Publicly Request Feedback in an Online Critique Community. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW2, Article 161 (oct 2020), 24 pages. https://doi.org/10.1145/3415232
[20] Eun Kyoung Choe, Nicole B. Lee, Bongshin Lee, Wanda Pratt, and Julie A. Kientz. 2014. Understanding Quantified-Selfers' Practices in Collecting and Exploring Personal Data. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI '14)*. Association for Computing Machinery, New York, NY, USA, 1143–1152. https://doi.org/10.1145/2556288.2557372
[21] Chia-Fang Chung, Elena Agapie, Jessica Schroeder, Sonali Mishra, James Fogarty, and Sean A. Munson. 2017. When Personal Tracking Becomes Social: Examining the Use of Instagram for Healthy Eating. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 1674–1687. https://doi.org/10.1145/3025453.3025747
[22] Nathalie Colineau and Cécile Paris. 2010. Talking about your health to strangers: understanding the use of online social networks by patients. *New Review of Hypermedia and Multimedia* 16, 1-2 (2010), 141–160. https://doi.org/10.1080/13614568.2010.496131 arXiv:https://doi.org/10.1080/13614568.2010.496131
[23] Munmun De Choudhury and Sushovan De. 2014. Mental Health Discourse on reddit: Self-Disclosure, Social Support, and Anonymity. *Proceedings of the International AAAI Conference on Web and Social Media* 8, 1 (May 2014), 71–80. https://doi.org/10.1609/icwsm.v8i1.14526
[24] Munmun De Choudhury, Mrinal Kumar, and Ingmar Weber. 2017. Computational Approaches Toward Integrating Quantified Self Sensing and Social Media. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing* (Portland, Oregon, USA) *(CSCW '17)*. Association for Computing Machinery, New York, NY, USA, 1334–1349. https://doi.org/10.1145/2998181.2998219
[25] Nicole B. Ellison, Jessica Vitak, Rebecca Gray, and Cliff Lampe. 2014. Cultivating Social Resources on Social Network Sites: Facebook Relationship Maintenance Behaviors and Their Role in Social Capital Processes*. *Journal of Computer-Mediated Communication* 19, 4 (07 2014), 855–870. https://doi.org/10.1111/jcc4.12078 arXiv:https://academic.oup.com/jcmc/article-pdf/19/4/855/22317768/jjcmcom0855.pdf
[26] Daniel A. Epstein, Alan Borning, and James Fogarty. 2013. Fine-Grained Sharing of Sensed Physical Activity: A Value Sensitive Approach. In *Proceedings of the 2013 ACM International Joint Conference on Pervasive and Ubiquitous Computing* (Zurich, Switzerland) *(UbiComp '13)*. Association for Computing Machinery, New York, NY, USA, 489–498. https://doi.org/10.1145/2493432.2493433
[27] Daniel A. Epstein, Clara Caldeira, Mayara Costa Figueiredo, Xi Lu, Lucas M. Silva, Lucretia Williams, Jong Ho Lee, Qingyang Li, Simran Ahuja, Qiuer Chen, Payam Dowlatyari, Craig Hilby, Sazeda Sultana, Elizabeth V. Eikey, and Yunan Chen. 2020. Mapping and Taking Stock of the Personal Informatics Literature. *PACM Interactive Mobile, Wearable and Ubiquitous Technologies (IMWUT)* 4, 4, Article 126 (Dec. 2020), 38 pages. https://doi.org/10.1145/3432231
[28] Daniel A. Epstein, Mira Dontcheva, James Fogarty, and Sean A. Munson. 2020. Yarn: Adding Meaning to Shared Personal Data through Structured Storytelling. *Proceedings of Graphics Interface (GI '20)* (2020). https://doi.org/10.

20380/GI2020.18

[29] Daniel A. Epstein, Bradley H. Jacobson, Elizabeth Bales, David W. McDonald, and Sean A. Munson. 2015. From "Nobody Cares" to "Way to Go!": A Design Framework for Social Sharing in Personal Informatics. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work amp; Social Computing* (Vancouver, BC, Canada) *(CSCW '15)*. Association for Computing Machinery, New York, NY, USA, 1622–1636. https://doi.org/10.1145/2675133.2675135

[30] Daniel A. Epstein, Siyun Ji, Danny Beltran, Griffin D'Haenens, Zhaomin Li, and Tan Zhou. 2020. Exploring Design Principles for Sharing of Personal Informatics Data on Ephemeral Social Media. *PACM Human-Computer Interaction* 4, CSCW2, Article 95 (Oct. 2020), 24 pages. https://doi.org/10.1145/3415166

[31] Daniel A. Epstein, Fannie Liu, Andrés Monroy-Hernández, and Dennis Wang. 2022. Revisiting Piggyback Prototyping: Examining Benefits and Tradeoffs in Extending Existing Social Computing Systems. *Proc. ACM Hum.-Comput. Interact.* 6, CSCW2, Article 456 (nov 2022), 28 pages. https://doi.org/10.1145/3555557

[32] Gunther Eysenbach, John Powell, Marina Englesakis, Carlos Rizo, and Anita Stern. 2004. Health related virtual communities and electronic support groups: systematic review of the effects of online peer to peer interactions. *BMJ* 328, 7449 (2004), 1166. https://doi.org/10.1136/bmj.328.7449.1166 arXiv:https://www.bmj.com/content/328/7449/1166.full.pdf

[33] Reza Farahbakhsh, Ángel Cuevas, and Noël Crespi. 2015. Characterization of cross-posting activity for professional users across major OSNs. In *2015 IEEE/ACM International Conference on Advances in Social Networks Analysis and Mining (ASONAM)*. 645–650. https://doi.org/10.1145/2808797.2809382

[34] Casey Fiesler and Brianna Dym. 2020. Moving Across Lands: Online Platform Migration in Fandom Communities. *Proc. ACM Hum.-Comput. Interact.* 4, CSCW1, Article 42 (may 2020), 25 pages. https://doi.org/10.1145/3392847

[35] Laura K. Gee, Jason Jones, and Moira Burke. 2017. Social Networks and Labor Markets: How Strong Ties Relate to Job Finding on Facebook's Social Network. *Journal of Labor Economics* 35, 2 (2017), 485–518. https://doi.org/10.1086/686225 arXiv:https://doi.org/10.1086/686225

[36] Carla F. Griggio, Midas Nouwens, Joanna McGrenere, and Wendy E. Mackay. 2019. Augmenting Couples' Communication with Lifelines: Shared Timelines of Mixed Contextual Information. In *Proceedings of the 2019 CHI Conference on Human Factors in Computing Systems* (Glasgow, Scotland Uk) *(CHI '19)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3290605.3300853

[37] Xinning Gui, Yu Chen, Clara Caldeira, Dan Xiao, and Yunan Chen. 2017. When Fitness Meets Social Networks: Investigating Fitness Tracking and Social Practices on WeRun. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 1647–1659. https://doi.org/10.1145/3025453.3025654

[38] Oliver L. Haimson, Jed R. Brubaker, Lynn Dombrowski, and Gillian R. Hayes. 2015. Disclosure, Stress, and Support During Gender Transition on Facebook. In *Proceedings of the 18th ACM Conference on Computer Supported Cooperative Work amp; Social Computing* (Vancouver, BC, Canada) *(CSCW '15)*. Association for Computing Machinery, New York, NY, USA, 1176–1190. https://doi.org/10.1145/2675133.2675152

[39] William A. Hamilton, Oliver Garretson, and Andruid Kerne. 2014. Streaming on Twitch: Fostering Participatory Communities of Play within Live Mixed Media. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI '14)*. Association for Computing Machinery, New York, NY, USA, 1315–1324. https://doi.org/10.1145/2556288.2557048

[40] Rebecca A. Hayes, Caleb T. Carr, and Donghee Yvette Wohn. 2016. One Click, Many Meanings: Interpreting Paralinguistic Digital Affordances in Social Media. *Journal of Broadcasting & Electronic Media* 60, 1 (2016), 171–187. https://doi.org/10.1080/08838151.2015.1127248 arXiv:https://doi.org/10.1080/08838151.2015.1127248

[41] Bernie Hogan. 2010. The Presentation of Self in the Age of Social Media: Distinguishing Performances and Exhibitions Online. *Bulletin of Science, Technology & Society* 30 (2010), 377 – 386.

[42] C. Hutto and Eric Gilbert. 2014. VADER: A Parsimonious Rule-Based Model for Sentiment Analysis of Social Media Text. *Proceedings of the International AAAI Conference on Web and Social Media* 8, 1 (May 2014), 216–225. https://doi.org/10.1609/icwsm.v8i1.14550

[43] Kevin O. Hwang, Allison J. Ottenbacher, Joseph F. Lucke, Jason M. Etchegaray, Amanda L. Graham, Eric J. Thomas, and Elmer V. Bernstam. 2011. Measuring Social Support for Weight Loss in an Internet Weight Loss Community. *Journal of Health Communication* 16, 2 (2011), 198–211. https://doi.org/10.1080/10810730.2010.535106 PMID: 21181600.

[44] Andreas M. Kaplan and Michael Haenlein. 2010. Users of the world, unite! The challenges and opportunities of Social Media. *Business Horizons* 53, 1 (2010), 59–68. https://doi.org/10.1016/j.bushor.2009.09.003

[45] Susie Khamis, Lawrence Ang, and Raymond Welling. 2017. Self-branding, 'micro-celebrity' and the rise of Social Media Influencers. *Celebrity Studies* 8, 2 (2017), 191–208. https://doi.org/10.1080/19392397.2016.1218292 arXiv:https://doi.org/10.1080/19392397.2016.1218292

[46] Joy Kim, Maneesh Agrawala, and Michael S. Bernstein. 2017. Mosaic: Designing Online Creative Communities for Sharing Works-in-Progress. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing* (Portland, Oregon, USA) *(CSCW '17)*. Association for Computing Machinery, New York, NY, USA,

246–258. https://doi.org/10.1145/2998181.2998195
[47] David S. Kirk, Abigail Durrant, Gavin Wood, Tuck Wah Leong, and Peter Wright. 2016. Understanding the Sociality of Experience in Mobile Music Listening with Pocketsong. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems* (Brisbane, QLD, Australia) *(DIS '16)*. Association for Computing Machinery, New York, NY, USA, 50–61. https://doi.org/10.1145/2901790.2901874
[48] Lindah Kotut, Michael Horning, Timothy L. Stelter, and D. Scott McCrickard. 2020. Preparing for the Unexpected: Community Framework for Social Media Use and Social Support by Trail Thru-Hikers. In *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (Honolulu, HI, USA) *(CHI '20)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3313831.3376391
[49] Yubo Kou and Colin M. Gray. 2018. "What Do You Recommend a Complete Beginner like Me to Practice?": Professional Self-Disclosure in an Online Community. *Proc. ACM Hum.-Comput. Interact.* 2, CSCW, Article 94 (nov 2018), 24 pages. https://doi.org/10.1145/3274363
[50] Yubo Kou and Xinning Gui. 2018. Entangled with Numbers: Quantified Self and Others in a Team-Based Online Game. *Proc. ACM Hum.-Comput. Interact.* 2, CSCW, Article 93 (nov 2018), 25 pages. https://doi.org/10.1145/3274362
[51] Nicole C. Krämer, Vera Sauer, and Nicole Ellison. 2021. The Strength of Weak Ties Revisited: Further Evidence of the Role of Strong Ties in the Provision of Online Social Support. *Social Media + Society* 7, 2 (2021), 20563051211024958. https://doi.org/10.1177/20563051211024958 arXiv:https://doi.org/10.1177/20563051211024958
[52] Tuck W. Leong and Peter C. Wright. 2013. Revisiting Social Practices Surrounding Music. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Paris, France) *(CHI '13)*. Association for Computing Machinery, New York, NY, USA, 951–960. https://doi.org/10.1145/2470654.2466122
[53] Victor Li, David W. McDonald, Elizabeth V. Eikey, Jessica Sweeney, Janessa Escajeda, Guarav Dubey, Kaitlin Riley, Erika S. Poole, and Eric B. Hekler. 2014. Losing It Online: Characterizing Participation in an Online Weight Loss Community. In *Proceedings of the 2014 ACM International Conference on Supporting Group Work* (Sanibel Island, Florida, USA) *(GROUP '14)*. Association for Computing Machinery, New York, NY, USA, 35–45. https://doi.org/10.1145/2660398.2660416
[54] Fannie Liu, Chunjong Park, Yu Jiang Tham, Tsung-Yu Tsai, Laura Dabbish, Geoff Kaufman, and Andrés Monroy-Hernández. 2021. Significant Otter: Understanding the Role of Biosignals in Communication. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Yokohama, Japan) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 334, 15 pages. https://doi.org/10.1145/3411764.3445200
[55] Zhe Liu and Bernard J. Jansen. 2013. Question and Answering Made Interactive: An Exploration of Interactions in Social QA. In *2013 International Conference on Social Intelligence and Technology*. 1–10. https://doi.org/10.1109/SOCIETY.2013.16
[56] Chen Lou and Shupei Yuan. 2019. Influencer Marketing: How Message Value and Credibility Affect Consumer Trust of Branded Content on Social Media. *Journal of Interactive Advertising* 19, 1 (2019), 58–73. https://doi.org/10.1080/15252019.2018.1533501 arXiv:https://doi.org/10.1080/15252019.2018.1533501
[57] Xi Lu, Yunan Chen, and Daniel A. Epstein. 2021. A Model of Socially Sustained Self-Tracking for Food and Diet. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2, Article 451 (oct 2021), 32 pages. https://doi.org/10.1145/3479595
[58] Kai Lukoff, Taoxi Li, Yuan Zhuang, and Brian Y. Lim. 2018. TableChat: Mobile Food Journaling to Facilitate Family Support for Healthy Eating. *Proc. ACM Hum.-Comput. Interact.* 2, CSCW, Article 114 (nov 2018), 28 pages. https://doi.org/10.1145/3274383
[59] Renkai Ma, Xinning Gui, and Yubo Kou. 2023. Multi-Platform Content Creation: The Configuration of Creator Ecology through Platform Prioritization, Content Synchronization, and Audience Management. Association for Computing Machinery, New York, NY, USA. https://doi.org/10.1145/3544548.3581106
[60] Haley MacLeod, Ben Jelen, Annu Prabhakar, Lora Oehlberg, Katie Siek, and Kay Connelly. 2016. Asynchronous Remote Communities (ARC) for Researching Distributed Populations. In *Proceedings of the 10th EAI International Conference on Pervasive Computing Technologies for Healthcare* (Cancun, Mexico) *(PervasiveHealth '16)*. ICST (Institute for Computer Sciences, Social-Informatics and Telecommunications Engineering), Brussels, BEL, 1–8.
[61] Lena Mamykina, Drashko Nakikj, and Noemie Elhadad. 2015. Collective Sensemaking in Online Health Forums. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 3217–3226. https://doi.org/10.1145/2702123.2702566
[62] Jennifer Marlow and Laura Dabbish. 2014. From Rookie to All-Star: Professional Development in a Graphic Design Social Networking Site. In *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work amp; Social Computing* (Baltimore, Maryland, USA) *(CSCW '14)*. Association for Computing Machinery, New York, NY, USA, 922–933. https://doi.org/10.1145/2531602.2531651
[63] Jennifer Marlow, Laura Dabbish, and Jim Herbsleb. 2013. Impression Formation in Online Peer Production: Activity Traces and Personal Profiles in Github. In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work* (San Antonio, Texas, USA) *(CSCW '13)*. Association for Computing Machinery, New York, NY, USA, 117–128.

https://doi.org/10.1145/2441776.2441792

[64] Alice E. Marwick and danah boyd. 2011. I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience. *New Media & Society* 13, 1 (2011), 114–133. https://doi.org/10.1177/1461444810365313 arXiv:https://doi.org/10.1177/1461444810365313

[65] Devadas Menon. 2022. Updating 'Stories' on social media and its relationships to contextual age and narcissism: A tale of three platforms – WhatsApp, Instagram and Facebook. *Heliyon* 8, 5 (2022), e09412. https://doi.org/10.1016/j.heliyon.2022.e09412

[66] Andrew D. Miller and Elizabeth D. Mynatt. 2014. StepStream: A School-Based Pervasive Social Fitness System for Everyday Adolescent Health *(CHI '14)*. Association for Computing Machinery, New York, NY, USA, 2823–2832. https://doi.org/10.1145/2556288.2557190

[67] Meredith Ringel Morris, Jaime Teevan, and Katrina Panovich. 2010. What Do People Ask Their Social Networks, and Why? A Survey Study of Status Message Qamp;a Behavior *(CHI '10)*. Association for Computing Machinery, New York, NY, USA, 1739–1748. https://doi.org/10.1145/1753326.1753587

[68] Florian Mueller, Frank Vetere, Martin R. Gibbs, Darren Edge, Stefan Agamanolis, and Jennifer G. Sheridan. 2010. Jogging over a Distance between Europe and Australia. In *Proceedings of the 23nd Annual ACM Symposium on User Interface Software and Technology* (New York, New York, USA) *(UIST '10)*. Association for Computing Machinery, New York, NY, USA, 189–198. https://doi.org/10.1145/1866029.1866062

[69] Sean A. Munson and Sunny Consolvo. 2012. Exploring goal-setting, rewards, self-monitoring, and sharing to motivate physical activity. In *2012 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth) and Workshops*. 25–32. https://doi.org/10.4108/icst.pervasivehealth.2012.248691

[70] Sean A. Munson, Erin Krupka, Caroline Richardson, and Paul Resnick. 2015. Effects of Public Commitments and Accountability in a Technology-Supported Physical Activity Intervention. In *Proceedings of the 33rd Annual ACM Conference on Human Factors in Computing Systems* (Seoul, Republic of Korea) *(CHI '15)*. Association for Computing Machinery, New York, NY, USA, 1135–1144. https://doi.org/10.1145/2702123.2702524

[71] Sean A. Munson, Debra Lauterbach, Mark W. Newman, and Paul Resnick. 2010. Happier Together: Integrating a Wellness Application into a Social Network Site. In *Proceedings of the 5th International Conference on Persuasive Technology* (Copenhagen, Denmark) *(PERSUASIVE'10)*. Springer-Verlag, Berlin, Heidelberg, 27–39. https://doi.org/10.1007/978-3-642-13226-1_5

[72] Elizabeth L. Murnane, Tara G. Walker, Beck Tench, Stephen Voida, and Jaime Snyder. 2018. Personal Informatics in Interpersonal Contexts: Towards the Design of Technology That Supports the Social Ecologies of Long-Term Mental Health Management. *Proc. ACM Hum.-Comput. Interact.* 2, CSCW, Article 127 (nov 2018), 27 pages. https://doi.org/10.1145/3274396

[73] Mor Naaman, Jeffrey Boase, and Chih-Hui Lai. 2010. Is It Really about Me? Message Content in Social Awareness Streams. In *Proceedings of the 2010 ACM Conference on Computer Supported Cooperative Work* (Savannah, Georgia, USA) *(CSCW '10)*. Association for Computing Machinery, New York, NY, USA, 189–192. https://doi.org/10.1145/1718918.1718953

[74] Mark W. Newman, Debra Lauterbach, Sean A. Munson, Paul Resnick, and Margaret E. Morris. 2011. It's Not That i Don't Have Problems, i'm Just Not Putting Them on Facebook: Challenges and Opportunities in Using Online Social Networks for Health. In *Proceedings of the ACM 2011 Conference on Computer Supported Cooperative Work* (Hangzhou, China) *(CSCW '11)*. Association for Computing Machinery, New York, NY, USA, 341–350. https://doi.org/10.1145/1958824.1958876

[75] Thi Thao Duyen T. Nguyen, Thomas Garncarz, Felicia Ng, Laura A. Dabbish, and Steven P. Dow. 2017. Fruitful Feedback: Positive Affective Language and Source Anonymity Improve Critique Reception and Work Outcomes. In *Proceedings of the 2017 ACM Conference on Computer Supported Cooperative Work and Social Computing* (Portland, Oregon, USA) *(CSCW '17)*. Association for Computing Machinery, New York, NY, USA, 1024–1034. https://doi.org/10.1145/2998181.2998319

[76] Midas Nouwens, Carla F. Griggio, and Wendy E. Mackay. 2017. "WhatsApp is for Family; Messenger is for Friends": Communication Places in App Ecosystems. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 727–735. https://doi.org/10.1145/3025453.3025484

[77] Yonggang Pan, Yunjie (Calvin) Xu, Xiaolun Wang, Chenghong Zhang, Hong Ling, and Jie Lin. 2015. Integrating social networking support for dyadic knowledge exchange: A study in a virtual community of practice. *Information Management* 52, 1 (2015), 61–70. https://doi.org/10.1016/j.im.2014.10.001

[78] Alexandra Papoutsaki, Samuel So, Georgia Kenderova, Bryan Shapiro, and Daniel A. Epstein. 2021. Understanding Delivery of Collectively Built Protocols in an Online Health Community for Discontinuation of Psychiatric Drugs. *Proc. ACM Hum.-Comput. Interact.* 5, CSCW2, Article 420 (oct 2021), 29 pages. https://doi.org/10.1145/3479564

[79] Kunwoo Park, Ingmar Weber, Meeyoung Cha, and Chul Lee. 2016. Persistent Sharing of Fitness App Status on Twitter. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work amp; Social Computing* (San Francisco, California, USA) *(CSCW '16)*. Association for Computing Machinery, New York, NY, USA, 184–194. https://doi.org/10.1145/2818048.2819921

[80] Sun Young Park. 2018. Social Support Mosaic: Understanding Mental Health Management Practice on College Campus. In *Proceedings of the 2018 Designing Interactive Systems Conference* (Hong Kong, China) *(DIS '18)*. Association for Computing Machinery, New York, NY, USA, 121–133. https://doi.org/10.1145/3196709.3196787

[81] James W. Pennebaker, Matthias R. Mehl, and Kate G. Niederhoffer. 2003. Psychological Aspects of Natural Language Use: Our Words, Our Selves. *Annual Review of Psychology* 54, 1 (2003), 547–577. https://doi.org/10.1146/annurev.psych.54.101601.145041 arXiv:https://doi.org/10.1146/annurev.psych.54.101601.145041 PMID: 12185209.

[82] Aare Puussaar, Adrian K. Clear, and Peter Wright. 2017. Enhancing Personal Informatics Through Social Sensemaking. In *Proceedings of the 2017 CHI Conference on Human Factors in Computing Systems* (Denver, Colorado, USA) *(CHI '17)*. Association for Computing Machinery, New York, NY, USA, 6936–6942. https://doi.org/10.1145/3025453.3025804

[83] Amon Rapp. 2018. Gamification for Self-Tracking: From World of Warcraft to the Design of Personal Informatics Systems. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–15. https://doi.org/10.1145/3173574.3173654

[84] Paul J Resnick, Adrienne W Janney, Lorraine R Buis, and Caroline R Richardson. 2010. Adding an Online Community to an Internet-Mediated Walking Program. Part 2: Strategies for Encouraging Community Participation. *J Med Internet Res* 12, 4 (17 Dec 2010), e72. https://doi.org/10.2196/jmir.1339

[85] Ethan Z. Rong, Mo Morgana Zhou, Ge Gao, and Zhicong Lu. 2023. Understanding Personal Data Tracking and Sensemaking Practices for Self-Directed Learning in Non-classroom and Non-computer-based Contexts. In *Proceedings of the 2023 CHI Conference on Human Factors in Computing Systems* (Hamburg, Germany) *(CHI '23)*. Association for Computing Machinery, New York, NY, USA, Article 718, 16 pages. https://doi.org/10.1145/3544548.3581364

[86] John Rooksby, Mattias Rost, Alistair Morrison, and Matthew Chalmers. 2014. Personal Tracking as Lived Informatics. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Toronto, Ontario, Canada) *(CHI '14)*. Association for Computing Machinery, New York, NY, USA, 1163–1172. https://doi.org/10.1145/2556288.2557039

[87] Bobby Rozzell, Cameron W. Piercy, Caleb T. Carr, Shawn King, Brianna L. Lane, Michael Tornes, Amy Janan Johnson, and Kevin B. Wright. 2014. Notification pending: Online social support from close and nonclose relational ties via Facebook. *Computers in Human Behavior* 38 (2014), 272–280. https://doi.org/10.1016/j.chb.2014.06.006

[88] Koustuv Saha and Munmun De Choudhury. 2017. Modeling stress with social media around incidents of gun violence on college campuses. *Proceedings of the ACM on Human-Computer Interaction* 1, CSCW (2017), 92.

[89] Koustuv Saha, Jordyn Seybolt, Stephen M Mattingly, Talayeh Aledavood, Chaitanya Konjeti, Gonzalo J. Martinez, Ted Grover, Gloria Mark, and Munmun De Choudhury. 2021. What Life Events are Disclosed on Social Media, How, When, and By Whom?. In *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (<conf-loc>, <city>Yokohama</city>, <country>Japan</country>, </conf-loc>) *(CHI '21)*. Association for Computing Machinery, New York, NY, USA, Article 335, 22 pages. https://doi.org/10.1145/3411764.3445405

[90] Lauren Scissors, Moira Burke, and Steven Wengrovitz. 2016. What's in a Like? Attitudes and behaviors around receiving Likes on Facebook. In *Proceedings of the 19th ACM Conference on Computer-Supported Cooperative Work & Social Computing* (San Francisco, California, USA) *(CSCW '16)*. Association for Computing Machinery, New York, NY, USA, 1501–1510. https://doi.org/10.1145/2818048.2820066

[91] Lauren E. Scissors and Darren Gergle. 2013. "Back and Forth, Back and Forth": Channel Switching in Romantic Couple Conflict. In *Proceedings of the 2013 Conference on Computer Supported Cooperative Work* (San Antonio, Texas, USA) *(CSCW '13)*. Association for Computing Machinery, New York, NY, USA, 237–248. https://doi.org/10.1145/2441776.2441804

[92] Suvi Silfverberg, Lassi A. Liikkanen, and Airi Lampinen. 2011. "I'll Press Play, but I Won't Listen": Profile Work in a Music-Focused Social Network Service. In *Proceedings of the ACM 2011 Conference on Computer Supported Cooperative Work* (Hangzhou, China) *(CSCW '11)*. Association for Computing Machinery, New York, NY, USA, 207–216. https://doi.org/10.1145/1958824.1958855

[93] Meredith M. Skeels, Kenton T. Unruh, Christopher Powell, and Wanda Pratt. 2010. *Catalyzing Social Support for Breast Cancer Patients.* Association for Computing Machinery, New York, NY, USA, 173–182. https://doi.org/10.1145/1753326.1753353

[94] Manya Sleeper, William Melicher, Hana Habib, Lujo Bauer, Lorrie Faith Cranor, and Michelle L. Mazurek. 2016. Sharing Personal Content Online: Exploring Channel Choice and Multi-Channel Behaviors. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 101–112. https://doi.org/10.1145/2858036.2858170

[95] Hyewon Suh, John R. Porter, Alexis Hiniker, and Julie A. Kientz. 2014. @BabySteps: Design and Evaluation of a System for Using Twitter for Tracking Children's Developmental Milestones. In *Proceedings of the SIGCHI Conference*

on Human Factors in Computing Systems (Toronto, Ontario, Canada) *(CHI '14)*. Association for Computing Machinery, New York, NY, USA, 2279–2288. https://doi.org/10.1145/2556288.2557386

[96] Lee Taber, Sonia Dominguez, and Steve Whittaker. 2023. Ignore the Affordances; It's the Social Norms: How Millennials and Gen-Z Think About Where to Make a Post on Social Media. *Proc. ACM Hum.-Comput. Interact.* 7, CSCW2, Article 311 (oct 2023), 26 pages. https://doi.org/10.1145/3610102

[97] Yoshimitsu Takahashi, Chiyoko Uchida, Koichi Miyaki, Michi Sakai, Takuro Shimbo, and Takeo Nakayama. 2009. Potential Benefits and Harms of a Peer Support Social Network Service on the Internet for People With Depressive Tendencies: Qualitative Content Analysis and Social Network Analysis. *Journal of Medical Internet Research* 11 (2009).

[98] Jr. Tandoc, Edson C, Chen Lou, and Velyn Lee Hui Min. 2018. Platform-swinging in a poly-social-media context: How and why users navigate multiple social media platforms. *Journal of Computer-Mediated Communication* 24, 1 (10 2018), 21–35. https://doi.org/10.1093/jcmc/zmy022 arXiv:https://academic.oup.com/jcmc/article-pdf/24/1/21/27610577/zmy022.pdf

[99] Nathan TeBlunthuis, Charles Kiene, Isabella Brown, Laura (Alia) Levi, Nicole McGinnis, and Benjamin Mako Hill. 2022. No Community Can Do Everything: Why People Participate in Similar Online Communities. 6, CSCW1, Article 61 (apr 2022), 25 pages. https://doi.org/10.1145/3512908

[100] Rannie Teodoro and Mor Naaman. 2013. Fitter with Twitter: Understanding Personal Health and Fitness Activity in Social Media. *Proceedings of the International AAAI Conference on Web and Social Media* 7, 1 (Aug. 2013), 611–620. https://ojs.aaai.org/index.php/ICWSM/article/view/14417

[101] Dirk O. Mügge Tobias Greitemeyer and Irina Bollermann. 2014. Having Responsive Facebook Friends Affects the Satisfaction of Psychological Needs More Than Having Many Facebook Friends. *Basic and Applied Social Psychology* 36, 3 (2014), 252–258. https://doi.org/10.1080/01973533.2014.900619 arXiv:https://doi.org/10.1080/01973533.2014.900619

[102] Dennis Wang, Marawin Chheang, Siyun Ji, Ryan Mohta, and Daniel A. Epstein. 2022. SnapPI: Understanding Everyday Use of Personal Informatics Data Stickers on Ephemeral Social Media. *Proc. ACM Hum.-Comput. Interact.* 6, CSCW2, Article 539 (nov 2022), 27 pages. https://doi.org/10.1145/3555652

[103] Xiaoqing Wang and Shannon Lantzy. 2011. A Systematic Examination of Member Turnover and Online Community Health. *International Conference on Information Systems 2011, ICIS 2011* 4. https://aisel.aisnet.org/icis2011/proceedings/onlinecommunity/25

[104] Donghee Yvette Wohn, Guo Freeman, and Caitlin McLaughlin. 2018. Explaining Viewers' Emotional, Instrumental, and Financial Support Provision for Live Streamers. In *Proceedings of the 2018 CHI Conference on Human Factors in Computing Systems* (Montreal QC, Canada) *(CHI '18)*. Association for Computing Machinery, New York, NY, USA, 1–13. https://doi.org/10.1145/3173574.3174048

[105] Donghee Yvette Wohn, Cliff Lampe, Jessica Vitak, and Nicole B. Ellison. 2011. Coordinating the Ordinary: Social Information Uses of Facebook by Adults. In *Proceedings of the 2011 IConference* (Seattle, Washington, USA) *(iConference '11)*. Association for Computing Machinery, New York, NY, USA, 340–347. https://doi.org/10.1145/1940761.1940808

[106] Paweł W. Wozniak, Anton Fedosov, Eleonora Mencarini, and Kristina Knaving. 2017. Soil, Rock, and Snow: On Designing for Information Sharing in Outdoor Sports. In *Proceedings of the 2017 Conference on Designing Interactive Systems* (Edinburgh, United Kingdom) *(DIS '17)*. Association for Computing Machinery, New York, NY, USA, 611–623. https://doi.org/10.1145/3064663.3064741

[107] Anbang Xu, Shih-Wen Huang, and Brian Bailey. 2014. Voyant: Generating Structured Feedback on Visual Designs Using a Crowd of Non-Experts. In *Proceedings of the 17th ACM Conference on Computer Supported Cooperative Work amp; Social Computing* (Baltimore, Maryland, USA) *(CSCW '14)*. Association for Computing Machinery, New York, NY, USA, 1433–1444. https://doi.org/10.1145/2531602.2531604

[108] Yu-Chun (Grace) Yen, Steven P. Dow, Elizabeth Gerber, and Brian P. Bailey. 2016. Social Network, Web Forum, or Task Market? Comparing Different Crowd Genres for Design Feedback Exchange. In *Proceedings of the 2016 ACM Conference on Designing Interactive Systems* (Brisbane, QLD, Australia) *(DIS '16)*. Association for Computing Machinery, New York, NY, USA, 773–784. https://doi.org/10.1145/2901790.2901820

[109] Wang Yuchao, Zhou Ying, and Zangyi Liao. 2021. Health Privacy Information Self-Disclosure in Online Health Community. *Frontiers in Public Health* (2021). https://doi.org/10.3389/fpubh.2020.602792

[110] Amy X. Zhang, Michael S. Bernstein, David R. Karger, and Mark S. Ackerman. 2024. Form-From: A Design Space of Social Media Systems. *Proc. ACM Hum.-Comput. Interact.* 8, CSCW1, Article 167 (oct 2024), 47 pages. https://doi.org/10.1145/3641006

[111] Xiaoquan (Michael) Zhang and Feng Zhu. 2011. Group Size and Incentives to Contribute: A Natural Experiment at Chinese Wikipedia. *American Economic Review* 101, 4 (June 2011), 1601–15. https://doi.org/10.1257/aer.101.4.1601

[112] Xuan Zhao, Cliff Lampe, and Nicole B. Ellison. 2016. The Social Media Ecology: User Perceptions, Strategies and Challenges. In *Proceedings of the 2016 CHI Conference on Human Factors in Computing Systems* (San Jose, California, USA) *(CHI '16)*. Association for Computing Machinery, New York, NY, USA, 89–100. https://doi.org/10.1145/2858036.2858333

[113] Xuan Zhao, Niloufar Salehi, Sasha Naranjit, Sara Alwaalan, Stephen Voida, and Dan Cosley. 2013. The Many Faces of Facebook: Experiencing Social Media as Performance, Exhibition, and Personal Archive. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Paris, France) *(CHI '13)*. Association for Computing Machinery, New York, NY, USA, 1–10. https://doi.org/10.1145/2470654.2470656

[114] Haiyi Zhu, Amy Zhang, Jiping He, Robert E. Kraut, and Aniket Kittur. 2013. Effects of peer feedback on contribution: a field experiment in Wikipedia. In *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Paris, France) *(CHI '13)*. Association for Computing Machinery, New York, NY, USA, 2253–2262. https://doi.org/10.1145/2470654.2481311

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