The Mechanisms and Conditions of End-User Manipulation in For-Profit Mobile Health Applications

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On my honor as a University student, I have neither given nor received unauthorized aid on this assignment as defined by the Honor Guidelines for Thesis-Related Assignments.

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Introduction

Mobile health (mHealth) is widely seen as a massive opportunity for improving individual health and well-being, as well as for capital investment (Arigo et al., 2019; Grundy, 2022). Broadly encompassing both smartphone applications (apps) and wearable health devices, mHealth is a rapidly growing field that is constantly introducing new technologies, conducting studies, and releasing products. My focus herein is on mHealth apps (specifically for-profit ones), which seek to leverage the ubiquity of smartphones as a means of enabling their end-users (here, 'users') to act healthy. A generic mHealth app is focused on enabling healthy activity at all times by tracking one or more aspects of an individual's health through a variety of on-device and external sensors or by relying on the user to self-report data, then using this information to provide personalized feedback, recommendations, goals, and more.

Given that the most popular mHealth apps are developed by large, for-profit corporations that accumulate a wealth of deeply personal health data with the explicit aim of influencing user behavior, critical studies have arisen to investigate the privacy concerns (Papageorgiou et al., 2018; Tangari, Ikram, Ijaz, Kaafar, & Berkovsky, 2021), conflicts of interest (Grundy, Held, & Bero, 2017), impacts (Charitsis, 2019; Grundy, 2022; Lupton, 2019), ethics (Herzog, Kellmeyer, & Wild, 2022), and motivations (Sax, 2021) surrounding mHealth apps. Motivated by these critical studies of mHealth applications and a social justice orientation, I apply feature analysis (Hasinoff & Bivens, 2021) to understand the *mechanisms* and *conditions* (Davis, 2020) through which the features of six top-grossing mHealth apps *afford* action to their users.[1] In this paper, I will argue that app store descriptions market features as a means of achieving a 'healthy' affect through habitual self-tracking, that apps primarily seek to afford data collection and analysis over

[1] That is, how these apps make particular actions available to different users within a social context.

behavior that positively impacts individual health outcomes, and that these affordances are largely legitimized by US social structure and often do not benefit all users equally.

In the subsequent sections, I first expand on the definition of mHealth apps, relevant research pertaining to their (mis)use of user data, what critical studies have already revealed about this technology, and the mechanisms and conditions framework for affordances that I utilize. Then, I articulate my methods, including a description of feature analysis and the mHealth apps I selected. Afterward, I discuss the results of my analysis in terms of the features, mechanisms, and conditions surrounding the affordances of mHealth apps. Last, I conclude with a summary of possible future work for legislators/regulators, users, developers, and researchers who wish to further social justice within mHealth apps.

Literature Review

mHealth apps widely employ a methodology called Digital Behavioral Technology (DBT; Grundy, 2022; Herzog et al., 2022). DBT involves analyzing passively- and actively-surveilled user data to understand individual behavior, then using this information to act back upon the user in a way that is intended to modify their behavior. In the context of health, user data can be highly sensitive and personal (e.g. menstrual cycle tracking, sexual activity) and changes in behavior towards normalized ideals of health may not necessarily benefit all individuals. Although they are explicitly health-focused, it is also important to mention that mHealth apps are not seen as medical devices and are therefore not regulated as such (Grundy, 2022). In practice, users' experience of mHealth DBT is mixed (Carter, Robinson, Forbes, & Hayes, 2018). The aspects of DBT that offer personalization and provide motivating feedback are largely seen as positive, but self-surveillance can lead to negative experiences (ranging from annoyance at manually entering data to feelings of shame or guilt). Additionally, the same study found that individual experiences with mHealth apps are impacted by a variety of personal factors (e.g. familiarity with health apps, motivation for use, ability to achieve goals). A review by Grundy (2022) further indicates that app users recognize how apps are "designed for a very particular use case (typically able-bodied people based in the United States), addressed a narrow range of experience, and required time-consuming, tedious, or complicated data entry" (p. 120; see also Lupton, 2019). Studies which explore user experiences with mHealth apps often provide little insight into data privacy and security, or the impact of wider socio-political environments on the user experience.

A separate corpus of literature shines a light on the first component of this gap: how mHealth apps track and share user data. Grundy, et al. (2021) argue that "health apps are just one source of user data that is collected, transmitted to third parties, then aggregated to create detailed impressions about users and people such as them" (p. 1). This claim is supported in a study by Tangari et al. (2021) which found that 88% of mHealth apps on the Google Play Store "could access and potentially share personal data" (p. 8) that is unique and persistent (e.g. contact information, location, and device identifiers). A similar percentage (87%) collected data for third party services, and 55.8% of observed user data transmissions were towards third parties. A separate study of 20 mHealth apps on the Google Play Store found that 50% of apps shared health data with third parties and 35% shared location data (Papageorgiou et al., 2018). This same paper found that several of the studied apps were not "GDPR ready", having violated at least one of the requirements of the European Union's data privacy legislation, and most did not follow "well-known" privacy and security guidelines (e.g. secure data transmission and storage protocols). Although mHealth apps were less likely to integrate 3rd party services for ads and tracking or collect personal identifiers than non-mHealth apps, an analysis of user reviews indicated that users had little awareness of their data collection and sharing practices (Tangari et al., 2021).

Grundy et al. (2017) argues that even in cases where individual health and fitness apps do not collect identifiable user data, the aggregation of personal and health data in the hands of a few dominant parties poses similar security and privacy concerns. While many such apps stand alone, a network analysis illustrated how 15 app families (determined by shared app ownership) “assumed more central network positions as gatekeepers on the shortest paths that data would have to travel between other app families” (Grundy et al., 2017, p. 1). The implication here is that companies such as Apple, Facebook, and Twitter are positioned to aggregate user information from several sources despite not even having dedicated mHealth apps (at the time of publication). In addition, Apple and Google can be seen as “the *de facto* regulators” in the market due to their ownership of distribution channels (Grundy, 2022, p. 121). Supporting this, Tangari et al. (2021) found that 70% of personal data collected by mHealth apps was collected by only 50 unique services. Of these, the most prominent was Google (likely a result of studying Google Play Store apps). The possibility of data aggregation raises concerns about the potential use of personal information (including health data) by third parties to make automated judgments about loans, employment, and more. Overall, the security, privacy, and tracking vectors of mHealth apps have been well-explored in the context of the app ecosystem, so what remains to be explored is the diverse ways in which users are impacted by apps themselves (and therefore the broader ecosystem the apps are situated within).

Referring to existing studies on the quality of mHealth apps, Grundy (2022) says “...we currently have a better idea of what apps are not rather than what they are” (p. 122), claiming that popular apps often do not implement evidence-based medicine, are not shown to result in positive health outcomes, and provide lackluster privacy and security. Lupton (2019) complements this by articulating how mHealth apps "enchant" users to notice, download, and use the app through features that promise self-discovery and improvement (among other things). Others have argued that the collection of health and personal data is not so much to optimize health as it is to optimize engagement, and for-profit mHealth apps abuse 'health' as an ideal to manipulate users into spending time and money on the app (Sax, 2021). To Grundy (2022), "documenting the composition, activities, and health impacts of the mobile ecosystem" (p. 127) has an opportunity to improve digital health equity.

To understand how the features of mobile health applications afford action to different users under different conditions, I will be using the Mechanisms and Conditions framework for affordances (M&C; Davis, 2020, 2023). M&C is an extension of affordances, the idea that a technology's features affect its use and function, which emphasizes *how* the technology affords social action (mechanics) as well as the diversity of *whom* the technology affords action for, under specific scenarios (conditions). It is therefore useful for understanding how sociotechnical systems like mHealth applications relate to larger structures of power and meaning. To be more specific, *mechanisms* are the variety of ways in which technologies *request* and *demand*, *encourage* and *discourage*, or *refuse* and *allow* social action. *Conditions* involve the *perception*, *dexterity*, and cultural and institutional *legitimacy* of the social structure in which the technology exists, and that influences its *mechanisms*.[2]

Following suggestions from Davis (2020), Grundy (2022), and Sax (2021), I will use M&C to analyze the features and data-sharing practices of popular mHealth applications,

[2] *Perception* refers to the knowledge held by a person about the functions of a technology, *dexterity* refers to the skill with which a person is able to operate the technology, and *legitimacy* refers to the support that a person does or does not have in operating the technology (Davis, 2020).

painting a picture of how the major players in the ecosystem afford action to users given the social context in which the apps exist.

Methods

I will conduct a feature analysis (Bivens & Hasinoff, 2018; Davis, 2020; Hasinoff & Bivens, 2021) of the top 6 grossing Health and Fitness apps on the Google Play Store in the United States: Fitbit, MyFitnessPal, Finch, Calm, AllTrails, and Flo. To identify features of each app that directly relate to the optimization of health and wellness, I will first analyze the descriptions of each app on the Google Play Store using CATMA (Gius et al., 2025), classifying and naming all uncovered features.[3] Then, I will categorize the affordances of common features according to their mechanisms and conditions. Specifically, I will consider the difference between the marketed intent of the feature and the range of condition-dependent outcomes, accounting for the broader social environment of the app and individual factors that determine its (dis)use.

Analysis

Features

The features marketed by the mHealth apps I analyzed overwhelmingly involved the persistent tracking and logging of user activity, motivated by the promise of imparting some affective experience or impactful feedback onto the user, which may require repeated engagement and/or direct payment for the user to access or realize. Firstly, app descriptions prominently referenced Tracking and logging features (Table 1). The specific nature of each Tracking feature varied. No one type of Tracking was shared by all apps, nor did one app reference each tracking feature. Fitbit and Flo mentioned the broadest range of Tracking features

[3] Descriptions for each app were collected on March 8th, 2025. Raw app description text and annotations are available at https://github.com/andbalch/thesis_data. Basic overviews of each app and tables summarizing features, examples, and which apps expressed them are provided in the Appendix.

in their descriptions, while Calm and Finch mentioned the most limited range. However, this is not to imply that apps with narrow Tracking features de-emphasized the behavior of tracking in general. Instead, Calm and Finch very intensely focused on stress- and mental health-focused Tracking. Common Tracking modalities were Activity (e.g. running), Stress (e.g. mental health quizzes, journaling), Diet (e.g. calorie-counting), and Weight tracking. Often, Tracking features were introduced in the context of the utility or benefit they would provide to the user (e.g. maintaining one's weight, understanding mental health trends).

Beyond tracking functionality, apps also marketed Developer and User-Generated Content (Tables 2 and 3). Goals and task-oriented exercises were a common theme among the analyzed app descriptions, which were often paired with messaging that emphasized repeated goal-setting, task-completing, or self-tracking within the app. Access to more traditional Content was also included as a feature, such as guided mindfulness sessions, health professionals or personal trainers, healthy recipes and workouts. Flo even marketed a "Symptom Checker Tool" as a unique feature of the app. It should be noted that several Content-related features require or present opportunities for data collection in ways that may be less apparent than Tracking-related features. For example, following a recipe or workout in an app thereby informs the app of the corresponding user behavior even without logging calories or recording physical activity. User-Generated Content was mentioned by half of the apps (AllTrails, Flo, and MyFitnessPal). This takes the form of information shared with other users (e.g. hiking trails or meal nutritional content), forums where users can discuss and ask questions, and reviews of in-app content.

Flo was the single app that described Privacy-related features (Table 3), however it was also the only app in this analysis which has had to settle a US Federal Trade Commission (FTC) complaint about sharing sensitive user health data with third-parties without their knowledge

(Federal Trade Commission, 2021). Flo offers an “Anonymous Mode” where potentially-identifiable information will “not be connected with [users’] health data”. Fitbit was also unique in its use of Proprietary Metrics (e.g. Daily Readiness Score; Table 4). These are metrics calculated from a variety of user data and meant to represent a more abstract aspect of user health, but the exact means of their derivation is unclear. Unlike traditional metrics like steps or heart rate, only one app (or developer) can provide the user with a proprietary metric. All apps mentioned some sort of Premium membership or in-app purchase (Table 5). Frequently, apps positioned monetary payment as a means to unlock additional features or content, positioned as additional tools for achieving the wellness goals espoused by an app. General allusions to an improved experience and ‘unlocked possibilities’ were also common, as were simple mentions of a premium membership or purchase opportunity. Only the description of AllTrails explicitly acknowledged the existence of in-app advertisements via marketing a premium subscription as a means to remove them.

Lower-level app features, especially those related to Tracking, were marketed in relation to higher-order feedback and affective experiences. Therefore, the feedback provided by an app and the affect it aims to elicit through its use can themselves be seen as features. All apps sought to provide Feedback for the user via at least one of analysis or guidance, but coaching was also a common form of Feedback (Table 6). Fitbit described all forms of Feedback except for guidance and reward, while Calm only offered guidance. All Feedback features attempt to impart the values of the application upon the user and seek behavior change or repetitive engagement in line with these values. For this reason, Feedback features must be understood in combination with the marketed affect of an app. Predominant Affects identified in app descriptions positioned the app as an informant (all apps) or partner that enabled personalization or physical health (Table 7). For a majority of apps, habit was central to their affective messaging, emphasizing routine, daily interaction as the most effective means to achieve wellness goals. Unique feature and branding decisions are also evident through an app's Affect. For example, AllTrails and Finch utilize adventure as a motif to accent their respective focus on outdoors activity and non-traditional mental healthcare. AllTrails intersects with Flo on community- and security-related messaging, while Finch branches out into gamification.

Mechanisms

The "mechanisms" aspect of M&C can help articulate how the features identified in app descriptions interact to afford social action upon users. Through their features, mHealth apps leverage data in an attempt to afford what the developers and society as a whole perceive as 'healthy' behavior. I argue that the mechanisms of mHealth affordances demonstrate that the collection and analysis of user data by an app is antecedent to any impact on user health and wellbeing.

First, apps must *request* the sharing of user data which is necessary to enable their features. In practice, this is done through the request of device permissions (e.g. to connect with a heart rate monitor) or requests for information (e.g. logging dietary intake, reviewing a hiking trail). Users can deny these requests, but apps also *demand* that user data be shared with them in the sense that the app's marketed features (including higher-level features of Affect and Feedback) cannot be meaningfully engaged with if the user does not share their data. Tracking, Proprietary Metric, User-Generated Content, and Feedback features in particular are only functional when user data is provided, and explicitly so. One may argue that this perspective cannot be extended to other feature types, but I will echo an earlier point that features which are related to or involve the collection of user data may not be explicitly marketed as "tracking".

Low-level, Developer Content features as benign as searching for a hiking trail or browsing a recipe communicate information about the user to the app (e.g. which trails are interesting, what food was consumed). The app (often discreetly) stores this data and leverages it to provide other lower-level features such as Tracking or more Content, as well as higher-level features such as Feedback and Affect. Therefore, even features like guided workouts or meditations cannot be engaged with by the user without providing the app with data, and thus constitute a *demand* of the technology even if they are presented to users as a *request*.

Next, app features *encourage* and *discourage* particular user behaviors. The former is the most visible, as app descriptions prominently featured language aimed at enticing users through Affect and explicitly described how repeated engagement with Feedback and lower-level features would elicit the Affective features (e.g. "...see the big picture on your health and fitness journey with the Fitbit app" [Fitbit]). This tendency follows neatly from mHealth apps' foundations in DBT (Arigo et al., 2019). Routine patterns of interaction with the app and its features, especially Tracking and Goal/Exercise features (e.g. journaling, diet logging), are therefore *encouraged* by the app (Gaudet, 2023). So is paying for Premium features, as Premium features are marketed as extensions and improvements to the affective experience (e.g. "...your annual subscription gives you more tools for more adventures" [AllTrails]). Actions that involve periodic or partial engagement with the app's features are therefore *discouraged* because the app cannot meaningfully provide higher-level features of Feedback or Affect under these usage conditions. For example, Finch tracks a usage 'streak' which will be broken when a user fails to use the app for a consecutive day. Perhaps a deeper reason for discouraging any break in the pattern of engagement is because such a break implies that the app can no longer collect user data, which it relies on to power its features and ultimately remain successful in the competitive marketplace.

To this point, it has not been discussed how the features of these mHealth apps contribute to 'healthy' user activity. I argue that apps *allow* a narrow notion of healthy activity. Healthy activity is ultimately defined by what the app itself can recognize and turn into data, and is performed by users through engagement with the app's features (e.g. "...monitor your diet and conquer your health goals" [MyFitnessPal]). Privacy is also *allowed* by the Flo app. However, this private activity is only limited to the separation of personally-identifiable data from health data. Lastly, health apps *refuse* user action that lies beyond their set of features. If an action cannot be translated into data and collected by an app, then that action cannot be recognized by the app and is thus not of any value. It follows that the numerous, varied, and individual actions which impact a particular user's wellbeing can never be fully afforded by the features of an mHealth app (Charitsis, 2019).

Conditions

The mechanics of mHealth apps are conditioned upon individual perceptions and dexterity, as well as the social structure the app is situated within. Following the frameworks set forth for M&C (Davis, 2020) and Feature Analysis (Bivens & Hasinoff, 2018; Davis, 2020; Hasinoff & Bivens, 2021) as well as research which has explored the varied social impacts of mHealth apps, I will theorize about how *perception*, *dexterity*, and *legitimacy* may shape how apps afford in their interactions with users. I argue that mHealth app features are designed around the social structures that legitimize them to guide users into their mechanisms of data collection by default. Perception and dexterity define the extent to which individual users of mHealth apps are able to resist this guidance, utilize the app for their own ends, and self-determine technological affordances. However, this systematically excludes some users from the positive affordances of mHealth apps, and can even perpetuate harms against them.

Perhaps the strongest condition upon the affordances of mHealth apps is *cultural and institutional legitimacy*, which I discuss from the standpoint of the United States. Most importantly, as user data has become a commodity, for-profit corporations are encouraged to collect as much data as possible (if not for sale or advertising, then for internal use in product engineering, to boost company valuation, etc.). The normalization of big data *legitimizes* the mentality among app users that data collection is something to be expected and tolerated. The use of mHealth apps is also highly *legitimized* by one's employer, doctor, therapist, insurance company, etc. (Charitsis, 2019; Gaudet, 2023). *Legitimacy* further extends beyond use to the values that underlie the features of the app. The descriptions of Fitbit and MyFitnessPal in particular *allow* the social ideal that one's weight is something to be managed ("Keep your diet in check…" [Fitbit]) and *encourage* the continuous task of managing weight ("Track progress toward your… weight loss goals with MyFitnessPal" [MyFitnessPal]) because the apps exist within a social structure that *legitimizes* neoliberal, utilitarian values of self-improvement. Whether these legitimized features and patterns of use afford action that actually contributes to individual health and well-being beyond increased activity levels is empirically unclear (Grundy, 2022; Molina & Sundar, 2020). Furthermore, mHealth app mechanics of collecting and analyzing user data may actually afford harm to users under certain social scenarios. For example, Torchinsky (2022) reports on concerns about the misuse of health data associated with menstrual cycles in a post-Roe v. Wade America.

Users' *perceptions* of mHealth app functions primarily determine whether the app affords action to the user. A particular user may see certain apps and their features (especially Affect) as more intrinsically valuable to their personal health and wellness goals (Lupton, 2018; Molina & Sundar, 2020). If so, the user will be more likely to *perceive* that the app is useful to their goals and will interact with the app and its features in the manner that is *encouraged* by its design. However, it may be the case that a user *perceives* some features as valuable and others as invaluable, leading to selective usage patterns which embrace some of the app's affordances but reject others. An app can also influence *perception* by advertising itself as aligned with user values (Sax, 2021) or by capturing these values altogether (Nguyen, 2024). In these scenarios, the user is susceptible to manipulation by the app. An app's policies and reputation surrounding data security and privacy is also critical, as this will impact how users *perceive* that their data will be used by an app (Spithoff et al., 2024). For example, Flo is the only app explicitly marketed for menstrual cycle tracking, the only app which has faced litigation due to data misuse, and the only app that markets its privacy-related features as a mechanism for *allowing* privacy.

The *dexterity* of a user is a strong indicator of mHealth app use and outcomes, but is also biased towards young, educated, and tech-literate individuals (Bol, Helberger, & Weert, 2018). I posit that the *dexterity* of a user also determines their ability to resist manipulation and data misuse by an app. Lupton (2018) describes how as "affective forces" drove users to engage with food-tracking apps, these users struggled with feelings of frustration, fear, and annoyance as a result of the app imposing its narrow view of healthy behavior onto them. A *dexterous* user who can navigate an app's mechanisms of affect is more able to utilize an mHealth app towards their own, self-defined ends. They may log some foods, but not others. Allow some permissions, and deny the rest. Pursue some Affect, while ignoring all else. Again, *dexterity* is socially stratified, and apps are designed to manipulate users that are non-dexterous. Some users may not even be able to participate in the healthy behavior *allowed* by apps (Charitsis, 2019), despite the prevalence of Affective features that elicit inclusivity and personalization. In this sense, *dexterity* is also biased towards the wealthy and the able-bodied.

Conclusion

I have argued that the six top-grossing Health and Fitness apps on the US Google Play Store sell users the idea that habitual engagement with their tracking-based features will empower them to be more ‘healthy’. In practice, users by default experience *de facto* commodification via apps’ processes of data-extraction resulting in disheartening and even harmful impacts, unless the user is one of a normative, privileged few who is able to realize a perceived benefit from the app. To transform the structures of power that perpetuate these exploitative dynamics (Balch, 2024), several avenues for change are available to legislators/regulators, users, developers, and researchers. For example, legislators can pass comprehensive data privacy and use policies which regulatory agencies can then enforce, while also investigating manipulative apps and breaking up health data monopolies. Users can interrogate whether the behaviours *encouraged* by an app *allow* them to work towards their individual health goals without *demanding* too much from them. Developers can co-design new technologies with historically marginalized groups to fundamentally prioritize non-normative ideals of wellbeing while minimizing self-tracking. Researchers can continue to illustrate the inequalities and biases of for-profit mHealth apps, and even collaborate to create emancipatory alternatives to the for-profit app ecosystem which implement not just co-design, but also design led by public health activists (Harrington, Favela, Sum, Fox, & Dombrowski, 2024).

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Appendix

App Overviews

- AllTrails contains hundreds of thousands of trail maps for hiking, biking, running, etc. Users can track their location and progress along a trail, submit reviews, report conditions, and publish new routes.
- Calm is a mindfulness app that contains guided meditation sessions, breathing exercises, bedtime music, sounds, and stories, and more.
- Finch 'gamifies' habitual self-care activities like journaling through a virtual pet. As users complete tasks and hit goals in the app, they get rewards and interact with the pet. Accessories and outfits can also be purchased for the pet.
- Fitbit (owned by Google) is an all-in-one fitness and health tracker, primarily focused on external wearable devices that track movement and activities.
- Flo is a "period, pregnancy, and cycle tracker", including weight, mood, and physical activity, featuring predictive calendars and interactive symptom quizzes.
- MyFitnessPal is another all-in-one fitness and health tracker, primarily focused on dieting and food intake logging.

Table 1: Tracking-Related App Features

Category	Feature	Example	Apps
Tracking	Activity	"AllTrails offers more than a running app or fitness activity tracker…" [AllTrails]	AllTrails, Fitbit, Flo, MyFitnessPal
	Advertising	"Remove occasional ads…" [AllTrails]	AllTrails

Table 1: Tracking-Related App Features			
	Communication	"Some Fitbit devices let you handle calls and texts right from your wrist so permissions might be required…" [Fitbit]	Fitbit
	Menstrual Cycle	"...tracking your period, ovulation, or pregnancy." [Flo]	Flo
	Diet	"...all-in-one food tracker, calorie counter, macro tracker…" [MyFitnessPal]	Fitbit, Flo, MyFitnessPal
	Location	"...track your GPS location…" [AllTrails]	AllTrails
	Physiology (heart)	"...keep tabs on your heart rate 24/7…" [Fitbit]	Fitbit
	Physiology (weight)	"Weight loss, weight gain, weight maintenance…" [MyFitnessPal]	Fitbit, Flo, MyFitnessPal
	Safety	"Keep loved ones in the loop with Live Share." [AllTrails]	AllTrails
	Sleep	"...measuring your sleep duration and sleep stages…" [Fitbit]	Fitbit
	Stress	"...understand your mental health with quizzes for anxiety, depression…" [Finch]	Calm, Finch, Fitbit, Flo
	Misc	"...track meditations." [Calm]	AllTrails, Calm, Fitbit, Flo, MyFitnessPal

Table 2: Developer Content-Related App Features			
Category	Feature	Example	Apps
Developer Content	Goals/ Exercises	"Habit Tracker: Set goals and celebrate wins…" [Finch]	AllTrails, Calm, Finch, Fitbit,

Table 2: Developer Content-Related App Features			
			MyFitnessPal
	Mindfulness	"...a full library of sessions that calm anxiety…" [Fitbit]	Calm, Finch, Fitbit
	Personal Training	"Learn from a Registered Dietician" [MyFitnessPal]	Calm, MyFitnessPal
	Recipes	"...access to easy, healthy recipes to help you reach your nutrition goals" [Fitbit]	Fitbit, MyFitnessPal
	Workouts	"...stretching exercises fill our extensive library." [Calm]	Calm, Fitbit, MyFitnessPal
	Misc	"Check if symptoms match… perimenopause with our Symptom Checker Tool" [Flo]	AllTrails, Calm, Finch, Flo, MyFitnessPal

Table 3: User-Generated Content-Related App Features			
Category	Feature	Example	Apps
User-Generated Content	Information	"Add Your Own Meals" [MyFitnessPal]	AllTrails, MyFitnessPal
	Forums	"...discuss intimate topics from fertility to birth control in our supportive global community." [Flo]	AllTrails, Flo, MyFitnessPal
	Reviews	"Find detailed reviews and inspiration from a community of trail-goers like you" [AllTrails]	AllTrails

Table 4: Privacy App Features		
Feature	Example	Apps
Privacy	"Your name, email address, and technical identifiers will not be	Flo

Table 4: Privacy App Features		
	connected to your health data in [Anonymous Mode]” [Flo]	

Table 5: Proprietary Metric App Features		
Feature	Example	Apps
Proprietary Metric	“Your Daily Readiness Score helps you understand when it’s time to go all out…” [Fitbit]	Fitbit

Table 6: Feedback-Related App Features			
Category	Feature	Example	Apps
Feedback	Analysis	“See carbs, fat & protein breakdown by gram or percentage…” [MyFitnessPal]	AllTrails, Finch, Fitbit, Flo, MyFitnessPal
	Coaching	“We’ll help you plan, live, and share your outdoor adventures.” [AllTrails]	AllTrails, Finch, Fitbit, MyFitnessPal
	Competition	“See how… you stack up to friends and family.” [Fitbit]	Fitbit
	Guidance	“...guided mood journal…” [Finch]	AllTrails, Calm, Finch, Flo, MyFitnessPal
	Reminder	“Receive notifications about ovulation, birth control…” [Flo]	Fitbit, Flo
	Reward	“[Your self-care pet will] return from adventures to share stories with you!” [Finch]	Finch

Table 7: Affect-Related App Features			
Category	Feature	Example	Apps
Affect	Adventure	"...chart your own course with confidence…" [AllTrails]	AllTrails, Finch, MyFitnessPal
	Community	"Join over 380 million members…" [Flo]	AllTrails, Flo, MyFitnessPal
	Game	"Complete quick self-care exercises to grow your pet, earn rewards, and improve mental health!" [Finch]	Finch
	Habit	"Me mindful in your daily routine and learn to calm your thoughts" [Calm]	Calm, Finch, Flo, MyFitnessPal
	Inclusivity	"...whether you're into weight loos or weight gain" [MyFitnessPal]	AllTrails, Calm, Flo, MyFitnessPal
	Informant	"...see how your activity, sleep, nutrition, and stress all fit together." [Fitbit]	AllTrails, Calm, Finch, Fitbit, Flo, MyFitnessPal
	Mental Health	"Meditate daily to relieve anxiety…" [Calm]	AllTrails, Calm, Finch, Fitbit
	Partner	"Meet your new self-care best friend!" [Finch]	AllTrails, Calm, Finch, Fitbit, Flo, MyFitnessPal
	Personalization	"Bring the gym home with a curated list of audio and video workouts" [Fitbit]	AllTrails, Calm, Finch, Fitbit, Flo, MyFitnessPal
	Physical Health	"...a fast route to fat loss…" [MyFitnessPal]	Calm, Finch, Fitbit, Flo, MyFitnessPal
	Security	"Safely discuss intimate topics…" [Flo]	AllTrails, Flo