

# A Content Analysis of Popular Diet, Fitness, and Weight Self-Tracking Mobile Apps on Google Play

Arthur Tham<sup>1</sup>, Lois Kim<sup>1</sup>, Sean Victory<sup>1</sup>,  
Yunan Chen<sup>1</sup>, Kai Zheng<sup>1</sup>, and Elizabeth V. Eikey<sup>2</sup>

<sup>1</sup>University of California, Irvine, Irvine, CA 92697, USA

<sup>2</sup>University of California, San Diego, La Jolla, CA 92093, USA  
eeikey@health.ucsd.edu

**Abstract.** Mobile health applications, especially diet, weight, and fitness apps, have become increasingly popular over the years. However, the content and quality of these apps is not well understood. In order to address this, we performed a preliminary content analysis of the diet, weight, and fitness mobile apps on the Google Play Store to better understand the features of such apps. We conducted a descriptive analysis of 159 relevant apps and analyzed the top free 15 for tracked indicators, goal setting, types of input, reminders and notifications, social and community features, and connecting to experts. Based on these preliminary findings, we identify gaps and discuss their importance to future research in this space.

**Keywords:** mHealth, Mobile App, Self-tracking, Personal Informatics, Google Play.

## 1 Introduction

Mobile health applications (apps) have become increasingly popular among users. According to Krebs and Duncan [12], over half of mobile phone users (58.23%) have downloaded a health app. Among these health apps, fitness and nutrition-related apps are the most common [12]. Despite their popularity, more research is needed to assess the quality of apps beyond ratings and reviews in app stores [24]. One way to assess quality is to examine app content because features can hinder adoption and long-term use. In fact, some research shows about half of mobile users (45.7%) stop utilizing apps due to hard-to-use features [12] and some users abandon apps because they lack desired features [15].

Researchers are recognizing the importance of assessing the content and quality of apps in various domains [7, 24]. These studies tend to analyze condition-specific apps or examine whether or not app features are backed by scientific evidence [9, 16, 21]. Those focusing on diet or nutrition, fitness, or weight loss tend to look at feature trends [6, 8, 14, 19, 26, 27]. Similar to these studies, we focus on the top apps but take a broad approach by looking at the types of features that may be useful in promoting app use, health outcomes, and well-being.

Understanding the current landscape of popular diet, fitness, and weight apps is important due to their large user base. We aim to provide information about these apps

not only to improve people’s understanding of what is currently available and what features are being used to promote health, but also to help people find apps that best fit their needs. Specifically, we want to understand what health features exist in current popular apps and how we can improve these apps based on previously performed research. In other words, we are drawing attention to possible gaps in widely available features in such apps. We identified two broad research questions (and some sub-questions) that guided this study:

***RQ1: What are the top apps for diet, fitness, and weight self-tracking available on Google Play?***

***RQ2: What are the non-paid for features of the top 15 free apps for diet, fitness, and weight self-tracking available on Google Play?***

- *RQ2a: What indicators can be tracked?*
- *RQ2b: Do apps include goal setting?*
- *RQ2c: Do apps require manual input?*
- *RQ2d: Do apps give reminders or notifications?*
- *RQ2e: Do apps allow users to communicate with or get support from others?*
- *RQ2f: Do apps allow users to connect to experts?*

## 2 Methods

We examined self-tracking apps that allow users to monitor or track diet, fitness, and/or weight. We focused on the Google Play Store due to its popularity and the number of apps available. According to Statista [18], the Google Play Store has 3.8 million apps compared to the Apple App Store, which has 2 million. Thus, we believe this is a good first step in understanding the landscape of apps available.

### 2.1 Inclusion and Exclusion Criteria

We defined self-tracking as both manual and passive input of data from the user and having a visual log or history of activities that the user has done. Our inclusion and exclusion criteria included:

- **Logging:** The app has a logging functionality where users can input their progress relating to exercise, weight, and/or food. The logging functionality must not be fully reliant on external apps and cannot consist of only a calculator that does not save its value to an in-app log.
- **Date:** The app must be updated on or after March 1st, 2016 to ensure that the apps are still relevant within the last two years at the time of data collection.
- **Ratings:** The app must have at least 100 user-generated ratings and reviews.

### 2.2 Search, Screen, and Analysis

On February 26, 2018, we conducted the automated search to retrieve all app information from our search query. We used the following search query: diet OR fitness OR exercise OR health OR weight OR nutrition. We utilized Facundoolano’s “Google-

Play-Scraper”, a Node.js open-source module that provided us with 250 apps with details from the Google Play Store. Then, we had two screening phases. For the first phase, a team of 3 individuals screened the 250 apps based on our inclusion and exclusion criteria using app descriptions and screenshots provided on Google Play. If we did not have full agreement, then the app was set aside for a second screening. In our second screening, apps were re-analyzed and then discussed among the group until we reached consensus. This resulted in a final set of 159 self-tracking apps for data analysis. After the screening phases, a set of the top 15 free apps were selected for full review based on the number of reviews. We believed the greater number of reviews reflected the apps’ popularity; ratings could be artificially inflated by a low number of reviews. Then the apps were divided among 3 individuals; each downloaded and used 5 apps and analyzed them for tracked indicators, goal setting, manual input, reminders and notifications, social and community features, and connecting with experts.

### 3 Results and Discussion

#### 3.1 Descriptive Analysis (RQ1)

One hundred fifty-nine apps were included in our descriptive analysis. Overall, there are significantly more free apps ( $n=152$ ) than paid ( $n=7$ ), with the paid apps ranging from \$0.99 to \$11.99 (mean=\$5.63). These numbers do not include free apps that have premium versions. Most apps were in the Health & Fitness category ( $n=150$ ), followed by Medical ( $n=5$ ). The app ratings (scale from 1 to 5) ranged from 2.5 to 4.9 (mean=4.29,  $SD=0.47$ ), and the number of reviews ranged from 103 to 1,766,614 (mean=69278.66,  $SD=183492.90$ ).

#### 3.2 Content Analysis of 15 Apps (RQ2)

For RQ2, we conducted a content analysis of 15 apps, as shown in Table 1. Of these, the average rating was 4.35 and the average number of reviews was 493,627. Table 2 summarizes our findings from the content analysis of these 15 apps.

**Table 1. Top 15 Diet, Weight, Fitness Apps on Google Play**

App Name	Rating	# of Reviews
1. Calorie Counter - MyFitnessPal	4.6	1766614
2. Runtastic Running & Fitness Tracker	4.5	795245
3. Nike+ Run Club	4.4	658790
4. Endomondo - Running & Walking	4.5	505013
5. Pedometer, Step Counter & Weight Loss Tracker App	4.6	492135
6. Runkeeper - GPS Track Run Walk	4.5	488098
7. 30 Day Fitness Challenge - Workout at Home	4.8	433249
8. 7 Minute Workout	4.5	391162
9. Samsung Health	4.2	363964
10. Fitbit	3.9	324558
11. Strava Running and Cycling GPS	4.5	309050
12. Nike Training Club - Workouts & Fitness Plans	4.6	244116
13. Google Fit - Fitness Tracking	3.9	237766
14. Runtastic PRO Running, Fitness	4.5	208017
15. Mi Fit	3.3	186630

**Table 2. Summary of Content Analysis of Top 15 Apps**

<b>Content / Features</b>	<b>Feature Description</b>	<b># with Feature</b>
<b>Tracked Indicators (RQ2a)</b>	<i>Exercise</i>	15
	<i>Diet or calories</i>	3
	<i>Weight</i>	14
	<i>Mental health and/or mood</i>	5
<b>Goal Setting (RQ2b)</b>		11
<b>Input (RQ2c)</b>	<i>Fully passive</i>	1
	<i>Manual or semi-passive</i>	13
	<i>Some passive with device sync</i>	13
<b>Reminders (RQ2d)</b>		12
<b>Social &amp; Community Features (RQ2e)</b>	<i>Friending in app</i>	11
	<i>Forums or online community</i>	10
	<i>Competitions</i>	10
	<i>News feeds</i>	10
	<i>Connecting with social media</i>	10
<b>Connect with Experts (RQ2f)</b>		1

**Tracked Indicators (RQ2a).** All the self-tracking apps analyzed allowed for users to track exercise (n=15) and most apps (n=14) tracked weight, which was expected and unsurprising given our focus. Unexpectedly, there were few apps that allowed diet or calorie tracking (n=3). This may be due to the tediousness of tracking food items, which could lead to app abandonment. Overall, the apps were lacking in tracking mental health (n=5). Apps that did allow users to track mental health tended to have aspects of the user rating or indicating how a user felt emotionally during or after exercising (i.e., mood). For example, Runkeeper, allowed the user to indicate through a range of expressive faces, ranging from angry to very happy, how the user felt after their run. Mental health and emotional well-being is an important indicator to track when measuring an individual's health, along with physical health, as prior research has shown that there is a relationship between mental health and both eating and exercise. Both Sominsky et al. [22] and Albrecht [1] discuss that stress and eating are linked, where stress leads to increased food intake, especially in women with low self-esteem. Other aspects of mental health like self-esteem can affect a person's levels of physical activity and thus also affect perceived physical fitness and body image [28]. Emotions have also been found to affect eating habits and vice versa [13]. Therefore, more apps may need to include mental health indicator tracking in order to support psychological well-being and improve outcomes.

**Goal Setting (RQ2b).** Eleven of the 15 apps allowed the user to set a goal of some sort. Fitbit is an example of an app that allows goal setting where users can set a variety of goals related to exercise (number of days per week, number of calories burned), and nutrition & body (number of calories, amount of water, weight, body fat percentage). According to Stretcher et al. [25], goal setting is a noteworthy behavior change technique that can motivate people to achieve a certain task. However, there is not much evidence regarding the effectiveness of goal setting in such apps; Shilts et al. [20] found that while there has been some success in users achieving positive results due to goal

setting, there is not enough evidence that goal setting alone improves users' physical health or affects their physical behavior. Murnane et al. [15] found in her study that less than 15% of health app users look for goal-setting as an important health app feature. Researches should thus try to study goal setting independently and the effectiveness of other behavior change techniques within apps when they study the quality of health apps overall.

**Manual vs. Passive Input (RQ2c).** Some diet, fitness, and weight self-tracking apps may be too burdensome for users by requiring manual tracking. To reduce burden, apps, and app developers may want to leverage more passive tracking. Only Nike Training Club and Pedometer Step Counter allowed for fully passive/automated input, while other apps (n=13) have either manual or semi-automated input. Most passive input was from physical fitness such as GPS or step tracking. Almost all apps (n=13) allowed for it to sync with other hardware devices, such as smartwatches, which then permits further automation of user data input. However, the addition of other devices increases the financial burden on users as it requires them to purchase other devices and tools. Research shows that users feel many different kinds of burdens when using mobile apps such as the difficulty of use burden, time and social burden, mental burden, etc. [10]. Too much burden on the user can then lead to app abandonment, as seen in [3], where the burden of food journaling caused people to stop using the app or the overall negative effects on the users from these burdens [10]. While passive tracking is common in certain types of exercise, having passive input may prove to be more challenging with diet tracking. Researchers have been exploring ways to make food tracking more lightweight and less burdensome on users such as a photo-based food journal suggested by Cordeiro et al. [4]. Another example to decrease the burden on the user with a semi-automated diet tracking is a crowdsource approach based on food photographs [17]. Based on these findings, more research is needed on how to most appropriately reduce burden while keeping users engaged.

**Reminders and Notifications (RQ2d).** Twelve of the 15 apps utilized reminders in some way. Reminders can be sent via email, push notifications, or in-app. The fact that reminders need to be implemented within apps could be related to the trend that unmotivated users could miss entries resulting in app abandonment, as found by Cordeiro et al. [3]. On the other hand, some users may not want to use an app on a daily basis, as doing so could also cause users to become obsessed with tracking, leading to unhealthy habits. Eikley et al. [5] reported that users with eating disorders track their diet and exercise obsessively, something that mobile health apps do not strive to do. The goal of mobile health apps is to support positive health habits. Thus, researchers need to examine how users utilize apps in terms of timely usage and understand when and to whom reminders should be deployed.

**Social and Community Features (RQ2e).** Thirteen of the 15 apps have at least one social or community feature. Such features include forums, news feeds, competitions, and friending other users in-app. Apps like Fitbit and Samsung Health allow users to friend people within the app and have friendly challenges or competitions. Users also

have the option of connecting to social media. This is an unsurprising finding, as evidence shows that social support may help people change their behaviors and achieve their goals. For instance, Kiernan et al. [11] found that women (71.6%) were more likely to lose weight if they felt frequent friend and family support, something that these apps attempt to promote with their community features. Future work should consider the pros and cons of these different types of social features and how to promote long-term engagement in social aspects that are associated with better outcomes.

**Connecting with Experts (RQ2f).** Only one app, Samsung Health, allows users to connect with an expert (only allowed for Samsung Devices) to discuss via video chat to discuss medical advice, as a paid service. This is interesting given the push for telehealth and patient-provider communication and interaction, as found by Spooner et al. [23]. Even though our analysis focused primarily on self-tracking weight, diet, and fitness, we were surprised to see that such apps do not feature an easy way to connect users to experts that can provide them with advice. Alencar et al. [2] found that telehealth interventions with an expert help users achieve their goals more than those who had no intervention, suggesting experts play an important role in goal achievement. Therefore, developers and researchers should consider ways to allow users an easy method of sharing their health data and interacting with experts within these health apps.

#### **4 Limitations and Future Work**

The tools we used to get the information from the Google Play Store only returned the top 250 apps related to our keyword search, so we could not extensively and exhaustively cover all apps. For our preliminary results, we only covered the apps in Google Play and not in iOS. Although we identified 159 apps to be self-tracking, we only conducted a detailed analysis of 15 so far, which may not fully encompass all trends in apps. There is also the possibility that we may have missed some relevant apps due to the keywords used. If this analysis were repeated, the results may differ due to the Google Play market changing frequently. Lastly, we primarily focused on free content in our more detailed analysis; it is possible that some features that are lacking are behind a paywall. We intend to address some of these limitations by investigating iOS apps, conducting a content analysis of more apps, and including paid features and apps in the analysis.

#### **5 Conclusion**

This paper contains findings from a content analysis of popular apps for self-tracking weight, diet, and/or fitness. We found that these apps have popular features that users may utilize to improve their health but there are some limitations in terms of what features are supported.

## Acknowledgments

This work was supported by the National Center for Research Resources, the National Center for Advancing Translational Sciences, and the NIH (UL1 TR001414). It is solely the responsibility of the authors and does not necessarily represent the official views of the NIH.

## References

1. Albrecht, A. 2014. The Effects of Self-Esteem and Stress on Eating Behaviours in Females. *The Huron University College Journal of Learning and*. 52, 1 (2014).
2. Alencar, M. et al. 2018. The efficacy of a telemedicine - based weight loss program with video conference health coaching support. *J Telemed Telecare*. 12, (2018), 17745471.
3. Cordeiro, F. et al. 2015. Barriers and Negative Nudges : Exploring Challenges in Food Journaling. (2015), 1159–1162.
4. Cordeiro, F. et al. 2015. Rethinking the mobile food journal: Exploring opportunities for lightweight photo-based capture. *Proceedings of the CHI Conference on Human Factors in Computing Systems* (Seoul, Korea, 2015), 1–10.
5. Eikev, E. V. and Reddy, M.C. 2017. “It’s Definitely Been a Journey”: A Qualitative Study on How Women with Eating Disorders Use Weight Loss Apps. *ACM CHI Conference on Human Factors in Computing Systems (CHI '17)* (Denver, CO, 2017), 1–13.
6. Franco, R.Z. et al. 2016. Popular Nutrition-Related Mobile Apps: A Feature Assessment. *JMIR mHealth and uHealth*. 4, 3 (2016), e85. DOI:<https://doi.org/10.2196/mhealth.5846>.
7. Grundy, Q.H. et al. 2016. Challenges in Assessing Mobile Health App Quality: A Systematic Review of Prevalent and Innovative Methods. *American Journal of Preventive Medicine*. 51, 6 (2016), 1051–1059. DOI:<https://doi.org/10.1016/j.amepre.2016.07.009>.
8. Higgins, J.P. 2016. Smartphone Applications for Patients’ Health and Fitness. *American Journal of Medicine*. 129, 1 (2016), 11–19. DOI:<https://doi.org/10.1016/j.amjmed.2015.05.038>.
9. Juarascio, A.S. et al. 2015. Review of smartphone applications for the treatment of eating disorders. *European Eating Disorders Review*. 23, (2015), 1–11. DOI:<https://doi.org/10.1002/erv.2327>.
10. Kientz, J.A. and Suh, H. 2018. Understanding and Assessing the User Burden of Urden of Mobile Apps. *GetMobile: Mobile Comp. and Comm*. 21, 4 (2018), 5–7. DOI:<https://doi.org/10.1145/3191789.3191791>.
11. Kiernan, M. et al. 2012. Social support for healthy behaviors: Scale psychometrics and prediction of weight loss among women in a behavioral program. *Obesity*. 20, 4 (2012), 756–764. DOI:<https://doi.org/10.1097/OGX.0000000000000256>.Prenatal.
12. Krebs, P. and Duncan, D.T. 2015. Health App Use Among US Mobile Phone Owners: A National Survey. *JMIR mHealth and uHealth*. 3, 4 (2015), e101. DOI:<https://doi.org/10.2196/mhealth.4924>.
13. Macht, M. 2008. How emotions affect eating: A five-way model. *Appetite*. 50, 1 (2008), 1–11. DOI:<https://doi.org/10.1016/j.appet.2007.07.002>.
14. Middelweerd, A. et al. 2014. Apps to promote physical activity among adults: a review and content analysis. *International Journal of Behavioral Nutrition and Physical Activity*. 11, (2014), 9. DOI:<https://doi.org/10.1186/s12966-014-0097-9>.
15. Murnane, E.L. et al. 2015. Mobile Health Apps: Adoption, Adherence, and Abandonment. *Adjunct Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing and Proceedings of the 2015 ACM International Symposium on Wearable Computers* (New York, NY, USA, 2015), 261–264.

16. Nicholas, J. et al. 2015. Mobile apps for bipolar disorder: A systematic review of features and content quality. *Journal of Medical Internet Research*. 17, 8 (2015). DOI:<https://doi.org/10.2196/jmir.4581>.
17. Noronha, J. et al. 2011. Platemate: Crowdsourcing Nutritional Analysis from Food Photographs. *Proceedings of the 24th Annual ACM Symposium on User Interface Software and Technology*. (2011), 1–12. DOI:<https://doi.org/10.1145/2047196.2047198>.
18. Number of apps available in leading app stores as of 1st quarter 2018: 2018. <https://www.statista.com/statistics/276623/number-of-apps-available-in-leading-app-stores/>. Accessed: 2018-06-01.
19. Rivera, J. et al. 2016. Mobile Apps for Weight Management: A Scoping Review. *JMIR mHealth and uHealth*. 4, 3 (2016), e87. DOI:<https://doi.org/10.2196/mhealth.5115>.
20. Shilts, M.K. et al. 2004. Goal setting as a strategy for dietary and physical activity behavior change: A review of the literature. *American Journal of Health Promotion*. 19, 2 (2004), 81–93. DOI:<https://doi.org/10.4278/0890-1171-19.2.81>.
21. Singh, A. et al. 2017. Are HIV Smartphone Apps and Online Interventions Fit for Purpose? *Proceedings of the 2017 International Conference on Digital Health - DH '17*. (2017), 6–15. DOI:<https://doi.org/10.1145/3079452.3079469>.
22. Sominsky, L. and Spencer, S.J. 2014. Eating behavior and stress: A pathway to obesity. *Frontiers in Psychology*. 5, MAY (2014), 1–8. DOI:<https://doi.org/10.3389/fpsyg.2014.00434>.
23. Spooner, K.K. et al. 2017. eHealth patient-provider communication in the United States: interest, inequalities, and predictors. *Journal of the American Medical Informatics Association : JAMIA*. 24, e1 (2017), e18–e27. DOI:<https://doi.org/10.1093/jamia/ocw087>.
24. Stoyanov, S.R. et al. 2015. Mobile App Rating Scale: A New Tool for Assessing the Quality of Health Mobile Apps. *JMIR mHealth and uHealth*. 3, 1 (2015), e27. DOI:<https://doi.org/10.2196/mhealth.3422>.
25. Strecher, V.J. et al. 1995. Goal Setting as a Strategy for Health Behavior Change. *Health Education & Behavior*. 22, 2 (1995), 190–200. DOI:<https://doi.org/10.1177/109019819502200207>.
26. Yang, C.H. et al. 2015. Implementation of behavior change techniques in mobile applications for physical activity. *American Journal of Preventive Medicine*. 48, 4 (2015), 452–455. DOI:<https://doi.org/10.1016/j.amepre.2014.10.010>.
27. Zaidan, S. and Roehrer, E. 2016. Popular Mobile Phone Apps for Diet and Weight Loss: A Content Analysis. *JMIR mHealth and uHealth*. 4, 3 (2016), e80. DOI:<https://doi.org/10.2196/mhealth.5406>.
28. Zamani Sani, S.H. et al. 2016. Physical activity and self-esteem: Testing direct and indirect relationships associated with psychological and physical mechanisms. *Neuropsychiatric Disease and Treatment*. 12, (2016), 2617–2625. DOI:<https://doi.org/10.2147/NDT.S116811>.