A Review of Gamified Fitness Tracker Apps and Future Directions

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ABSTRACT

This review examines 103 existing gamified fitness tracker apps in the Apple App Store and Google Play Store that motivate users to walk more. We consider different types of game elements in these mobile app games and show how they cluster into different game genres. We found co-occurrences of various game elements including Competition, Challenges, and Social Influence. Social features played a central role in nearly every type of gamified fitness tracker app, where a sub-category of games with real-world incentives emerged. Content and network analysis are used to suggest new areas of the design space that are unexplored, but potentially fruitful, such as plot-based collaborative games.

CCS CONCEPTS

• **Human-centered computing** → *Ubiquitous and mobile devices.*

KEYWORDS

game; gamification; fitness tracker; exergames;activity tracker; fitness apps; step counter games

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1 INTRODUCTION

Personal activity trackers, such as Fitbit, Jawbone, and those built into smartphones and smartwatches, are increasingly being used to support personal data-driven games. An activity or fitness tracker is a wearable device that tracks users' activities and vitals such as step count, heart rate and sleep quality. Fitness trackers are being widely adopted with an estimated 104 million units of fitness tracker devices that will be shipped worldwide by 2022 [17], in addition to the fitness tracker features built into nearly all smartphones and smartwatches. Since their inception, activity trackers have used gamification techniques (i.e., used game elements in non-game contexts [18]). For example, the Fitbit app includes leaderboards (see Figure 9), competitive challenges (e.g. 'Weekend Warrior' which compares total step count over the weekend), and adventures that show images of famous hikes based on your distance. While researchers have prototyped novel games and gamification elements related to fitness trackers for over a decade (e.g., Ubifit [14]), it is not clear which game elements and designs have worked their way into commercial apps or what areas of the design space are still unexplored.

Gamified Fitness tracker apps are important to understand, in part because of their significant potential to improve public health. Exercise is a key component of a healthy lifestyle. Higher levels of physical activity are associated with lower mortality risks [26, 47]. The U.S. Department of Health and Human Services recommends a minimum of 150 to 300 minutes of moderate intensity activity each week for all healthy adults [46]. An estimation analysis found that decreasing the world's physical inactivity by 25% could avert more than 1.3 million preventable deaths worldwide every year [33].

Game elements that rely on activity data are also important to examine because they can lead to continued use of fitness trackers. Although the rate of fitness tracker adoption is increasing rapidly, people often stop using these devices relatively soon after purchasing them. Researchers have uncovered a number of reasons including (but not limited to): lack of ongoing health motivation, lack of interest in the functionality the devices provide, forgetting to wear it, and inconvenience of managing the device [12, 48]. This is unfortunate, since continued daily use of fitness trackers is associated with higher exercise motivation and awareness of physical activity [54]. Creating compelling games that leverage activity tracker data may provide increased motivation, enjoyment, and a reason to remember one's device.

Finally, fitness trackers also provide novel affordances for gameplay that may lead to new ways of having fun, irrespective of their impact on health. Activity tracking games fit well within the broad umbrellas of mixed reality games [27] and pervasive games [1, 42]. These games"expand the contractual magic circle of play spatially,

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temporally, or socially" [42] by creating "technology-mediated, playful experiences that are interwoven throughout our everyday lives and the physical and virtual spaces we inhabit" [1]. While insights from these high-level genres help us understand the challenges associated with blending game mechanics into everyday life, they don't provide sufficient granularity to inform the design of sub-genres such as activity tracker games. Prototype activity tracker games such as Fish n' Steps [35], Ubifit Garden [14], Houston [13], StepStream [40], Shakra [3], NEAT-o-Games [24], and American Horse Power Challenge [61] discussed in the following section, suggest promising game mechanics for activity tracker games. However, we still don't know fundamental questions about activity tracker games: How can we translate existing game mechanics (e.g., points, levels, unlockable content) into a fitness tracker game effectively? What novel activity-based mechanics are fun? Which mechanics fit well together? Addressing all of these questions is beyond the scope of a single paper, but it points to the importance of understanding the design space for activity tracker games.

The goal of this paper is to characterize the design space of commercially available fitness tracker games. Specifically, we aim to identify the core game elements of commercial apps, as well as examine their relationships with each other and various outcome metrics (e.g., number and quality of ratings). This analysis can help identify which game elements are most common, as well as how they cluster into game genres. This will form a baseline for future research that can track the evolution of these game genres. It can also help identify popular activity tracker game genres and gaps in the design space that may be ripe for innovation. In short, we address the following research questions:

(1) What game elements do commercial activity fitness tracking apps utilize?
(2) How do game elements relate to ratings and popularity?
(3) How do different game elements cluster and relate to one another?
(4) What areas of the design space are still unexplored?

2 PREVIOUS WORK

Previous research work on gamified fitness tracker apps has mostly focused on developing and evaluating particular types of gameplay mechanics and game elements. For instance, games like Fish n' Steps [35] and Ubifit Garden [14] utilize reward-based game elements like badges or a growing virtual garden, whereas games like StepStream [40], Houston [13], and Shakra [3] use the concept of passive competition through comparison with other users. Then, there are some games like NEAT-o-Games [24] and American Horse Power Challenge [61] that promote direct competition between users. While these prototype games help understand the theoretical implications and possibilities of various design choices, they fail to show how users react "in the wild" to various game mechanics. Most studies include dozens or hundreds of users, not thousands or tens of thousands of users. Exploring existing apps, as we do in this paper, helps to view activity tracker games from a different lens.

Previous research on classifying fitness related apps primarily examines the behavioral theories and techniques embedded into apps [16, 19, 39]. These studies find that only a small subset of behavior theories are embedded into fitness apps. For example, Cowan et al. (2013) found that fitness apps only contained minimal use of behavioral change theories [16]. A small set of other papers have explored game elements that are part of fitness apps. Kappen et al. (2017) performed a survey of gamification elements categorized by motivational affordances for different age groups [31]. They found that younger people prefer game elements with an ability to provide them quicker feedback, whereas middle-aged groups prefer game mechanics that allow them to set their own goals instead. Lister et al. (2014) examined gamification elements for classification apart from behavior change theories, but the sample was limited to iOS apps available in the winter of 2014 [36]. Building upon this work, a recent systematic survey analyzed the presence of gamification elements and use of behavioral economics principles [15]. Although it provided a good base for coding game elements, the sample of apps for that research only included the top 50 apps in the "Health and Fitness" category of the Apple App Store. Another limitation in this line of research is the miscategorization of apps [59], so it is essential that research look for apps in other categories as well. Furthermore, our focus is on fitness apps that utilize fitness data (operationalized as step-count data), not general-purpose fitness apps, which can be so diverse as to make comparisons less meaningful. This work is novel in two primary ways:

(1) The analysis provided comprehensive coverage of iOS and Android fitness apps that use step-count data as part of a game or gamification system.
(2) The analysis focuses on game design elements and their co-occurrence, rather than behavioral health impacts.

3 METHODS

We used a mixed-method approach to systematically examine the use of gamification elements in step-counter apps. This included identifying relevant apps, coding for game elements, relating them to performance metrics (number of reviews and review scores), and performing a network analysis to explore the relationship between game elements and identify gaps in the design space.

3.1 Identifying Gamified Fitness Tracker Apps

We followed the PRISMA [41] systematic review process to create a complete list of fitness tracker apps with game elements. Since we were reviewing apps instead of journal articles, the process was slightly modified as described in the following sections. A summary of the selection and filtering process is shown in Figure 1.

Our first step was to identify iOS and Android apps that use step-count data from fitness trackers or built-in smartphone pedometers. For the purposes of this paper, we define fitness tracker game apps narrowly to include only those apps that use step-count data. As a result, we skip apps like Strava that use other sensors, for instance, GPS, to track distance walked, biked, etc. We performed systematic searches on the Google Play Store, Apple App Store and app aggregator sites including AppGroves, AppBrain and AppAgg. To build an initial list of apps, we used the following search keywords related to fitness apps: *"fitness", "fitness game", "fitbit goal", "pedometer game", "step counter game", "fitbit game", "walk gamify", "garmin game", "fitness tracker game", "exergame"*. We developed these keywords by looking at common keywords used by widely popular

Table 1: Codebook of game elements and their description

Game Element	Description
Goals	Measurable and well-defined target that a user has to achieve.
Challenges	They are like goals or competitions but short-lived. They are sometimes optional in the games (like a side quest) or could be a challenge that moves a story forward. Also, code for challenge when the app explicitly identifies something as a "challenge."
Competition/Leaderboards	Compete with other members directly or through leaderboards.
Collaboration	Work together towards a common goal or objective in the game.
Social Influences	Performance is publicly displayed. Code for this if game activities can be shared or there are elements of peer pressure and social nudging.
High Scores	Tracking of best attempts over a particular timeframe.
Badges	Visual recognition earned for completing specific milestones, tasks or when player completes a goal or challenge.
Plot	Includes a pattern of events (i.e., causal chain of events) related to an unfolding narrative.
Narrative	Includes a theme that ties to an alternate world distinct from the everyday experience of the players. If an avatar of any kind is included in an app, the app will also have the Narrative classification.
Points	Accumulates points that help progress through game and/or can be redeemed for rewards or be used in in-game economy.
Levels	Progress through parts of the game (e.g. level 1 to level 2) or gradients of status (e.g. bronze level to silver level).
Unlockable Content	Access to enhanced functionality (new levels, gameplay, etc) or content for accumulating experience or achieving a specific goal.
Real-life Incentives	Discounts, rewards, donations, or prizes in real-life.

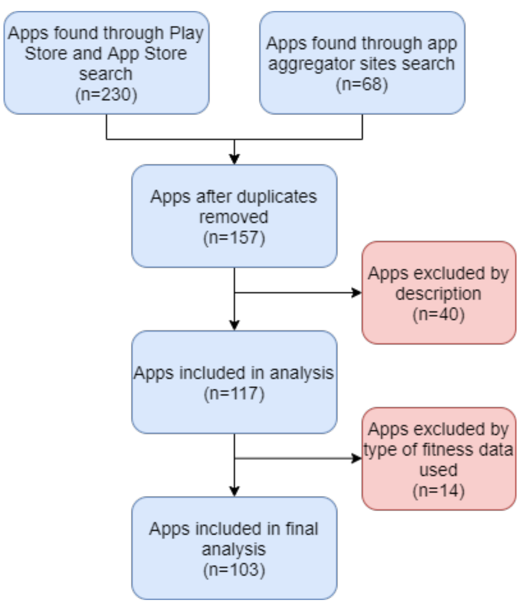

Figure 1: Selection and filtering process.

games, 'Wokamon', 'The Walk: Fitness Tracker Game', 'Zombies, Run!' [52], and 'Fitness RPG', and related games found by going through recommendations from these games in app stores. We also searched for apps using the names of popular fitness trackers in the market [28] including: *"fitbit", "garmin fitness tracker", "Huawei band", "moov fitness tracker", "Samsung galaxy fit"*.

Next, we expanded our list of apps by adding apps that were recommended by the app stores and app aggregator sites. For example, on the app page for a selected app (using the aforementioned searches), we would look at the apps in the Google Play Stores "Similar Apps," and in the Apple Store at the apps in the "You might also like" section. From our initial apps identified by keywords, we followed these "recommended apps," and analyzed two levels deeper for all apps we initially classified, or until all apps in the list were already included, whichever came first.

3.2 Narrowing to Step-Counter Apps

Next, we excluded apps that did not use step-count data to promote physical activity. Some of our initially identified apps used other fitness tracker data (e.g., sleep data; heart-rate information), but not step-count data. These apps were excluded from this paper after we identified their mode of tracking. For this study we limited our survey to apps that use fitness trackers with the base functionality of step counting. This ensures that all apps we reviewed have data about "steps taken" in common. Most of the apps mentioned what kind of tracking methods (e.g., step-count vs GPS) they used, but some apps had to be installed to identify that. Many excluded apps were virtual gym apps that connected people with fitness trainers, health coaches, etc. Others were diet and weight loss loggers that focused on calories burned (based on activity tracker data), but not steps. The number of apps excluded by this criteria is also shown in Figure 1 as "excluded by type of fitness data used". We did not include the exact number of exclusions for each fitness data types (such as GPS) because it could give the false impression that there are not apps with that characteristic in the app stores.

We also excluded a handful of apps only available to those who are part of a specific company or insurance plan (e.g., flexPoints, P2Pgo), since we were unable to consistently evaluate them without corporate credentials.

Finally, we excluded all fitness tracker apps that did not include any game elements or use step-count data for any game mechanics, as identified during our coding for game elements described next. All exclusions apart from the type of the fitness data used is captured as "excluded by description" in the figure.

3.3 Coding for Game Elements

We reviewed several game element taxonomies that fit the types of gamified fitness tracker apps selected via the previously described process. Ultimately, we combined two taxonomies of game elements based on work by Cotton and Patel, and Kappen et al. [15, 31] into a codebook. We conducted several rounds of iterative coding of random subsets of apps in order to refine our initial codebook. In total, three individuals performed coding during this process, with input from two others. Coders discussed discrepancies and possible solutions, recoded new subsamples, and repeated the process until the codebook was in its final state as shown in Table 1. The primary changes made from the initial taxonomy included the addition of two new game elements ("Real-life Incentives" and "Plot") and more details added to some categories such as "Challenges".

Using the final codebook, two authors independently coded all of the 103 apps, with 40% ($n = 43$) overlap in order to calculate inter-rater reliability using the Cohen's Kappa coefficient (k). Because each game element category is not mutually exclusive, k values were calculated for each category: Goals ($k = 0.90$), Challenges ($k = 0.72$), Competition/Leaderboards ($k = 0.85$), Collaboration ($k = 0.72$), Social Influences ($k = 0.82$), High-scores ($k = 0.86$), Badges ($k = 0.85$), Plot ($k = 1$), Narrative ($k = 0.95$), Points ($k = 0.76$), Levels ($k = 0.94$), Unlockable Content ($k = 0.86$), and Real-life Incentives ($k = 0.89$). We deemed these scores sufficiently high based on standard interpretations of these values [38]. At this point, the two raters met and came to a consensus after discussing any discrepancies in the 43 apps they both rated. This process was performed over a 4-month period starting mid-December 2019 through mid-April 2020.

We added additional data from the app stores including average review rating (1-5 stars), number of reviews, and category of app (e.g., "Health & Fitness"; "Games"). Data on the number of downloads is not available on the app stores, so we used the number of reviews as a proxy for popularity in our analysis. For apps available in both platforms, we used a weighted average of the ratings between the two stores based on the number of reviews that each had in. For popularity analysis, we skipped apps which had less than 30 reviews because we observed that a lot of initial reviews were fake positive reviews with 5-stars rating.

3.4 Game Element Co-Occurrence Network Analysis

We performed a network analysis and visualization of the data to better understand how game elements relate to one another within apps. We modeled game elements as vertices, with weighted edges representing the number of games that include the two game elements they are connecting. Apps having both iOS and Android versions were counted as a single app during this game element analysis. Visualizations were created using NodeXL [25]. In some visualizations, edges were filtered to remove less important connections between game elements. Details are provided in the Results section next to the images to enhance readability and comprehension of the graph.

When working with network data it is possible to use community detection algorithms to objectively identify groups of nodes that are highly interconnected [32]. We used the Louvain Community Detection algorithm, which attempts to maximize the modularity of the graph, because it works well with weighted networks [7]. Specifically, we used the python-louvain Community API that works with the NetworkX graph analysis python tool [5]. The output of the analysis identifies which game elements are tightly coupled with one another into sub-groups, based on the existence and weights of the various edges.

4 RESULTS

4.1 Overview of Game Data

In total, we analyzed 103 gamified fitness tracker apps that included step-count data and at least one game element. 80% (n=82) of them were available for the Android platform and 76% (n=78) of them were available for the iOS platform. As shown in Figure 2, they varied considerably in quality (rating from 1-5) and popularity (estimated by the total number of reviews). As expected, there was a power-law distribution of popularity; a relatively small number of games account for the vast majority of reviews, and a large number of games have few reviews. To better visualize the data on the number of reviews, the y-axis for the number of reviews uses a logarithmic scale. Although games that had ratings on both stores are counted separately for this analysis, it's worth nothing that the average rating for iOS based apps is higher than that for Android-based ones which is an interesting departure from the norm where Android apps often get rated more favorably than their iOS counterpart. [2, 29].

The most popular apps are shown at the top of Table 3 found at the end of the paper, which shows the most popular apps sorted by number of reviews. Even a simple review at the 10 most popular apps illustrates the diverse ways that game elements are incorporated into fitness tracker apps. Three of the most popular 10 gamified fitness tracker apps are the official app of a specific fitness tracker: Mi Fit [4], Fitbit [20], VeryfitPro [53]. These vary considerably in the level of gameplay they support with Fitbit including many types of game elements (e.g., group competitions, leaderboards, badges, journeys) and the other two including very limited gameplay options. Three other apps in the top 10 provide real-world incentives for taking steps: Charity Miles [10], Sweatcoin Pays You To Get Fit [55], and Yodo Cash for Running [62]. These also vary

Game Element	Count	No. of Game Elements	Rating (Avg.)	Rating (σ)	No. of Reviews (Median)	Total Reviews
Social Influences	69	5.25	3.95	0.70	202	3772994
Goals	63	4.89	3.98	0.64	163	3872679
Challenges	53	5.75	4.03	0.56	132	2445588
Real-life Incentives	48	4.44	3.96	0.67	332.5	510038
Competition	48	5.90	3.97	0.70	126.5	2436252
Points	47	5.98	3.93	0.65	202	318981
Narrative	34	5.94	4.00	0.65	79.5	858347
Collaboration	29	6.24	3.85	0.69	98	119856
Levels	22	6.86	4.08	0.51	84.5	826489
High Scores	20	5.60	4.00	0.51	145	909561
Unlockable Content	18	6.33	4.21	0.34	238.5	175574
Badges	14	6.71	4.28	0.36	1713	1537772
Plot	8	6.63	4.26	0.16	38	38870

Table 2: Statistics for apps containing each game element

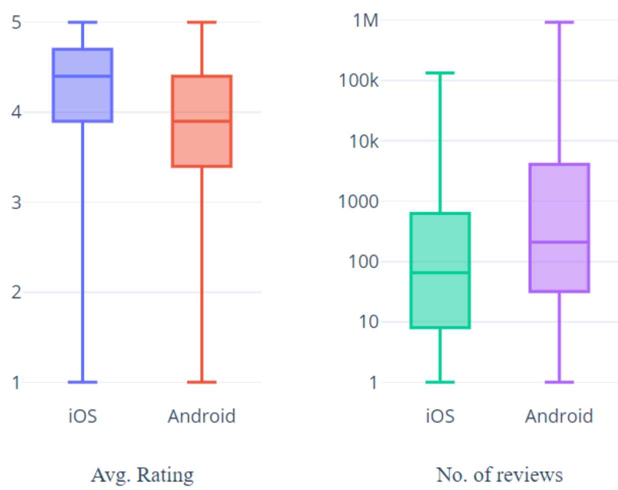

Figure 2: Quality and popularity metrics in app stores

considerably in the amount of game elements they support. Another three of the top 10 apps should be considered full games as opposed to gamified fitness apps: Zombies Run! (see Figure 8) [52], Walkr: Fitness Space Adventure [23], and Fit the Fat 2 [22]. These apps illustrate that some fitness tracker games include sophisticated game mechanics that integrate fitness into novel, playful experiences. For example, Walkr: Fitness Space Adventure includes a developed narrative that transforms steps into fuel for your rocket that allows you to explore the universe, collect planets, and collaborate with others to solve missions. The following sections will dive deeper into the various types of game elements that occur in the entire list of gamified fitness tracker apps and their relationships with each other.

4.2 Game Element Occurrences

We found evidence of all 13 game elements in the 103 gamified fitness tracker apps we evaluated. The distribution of game elements is shown in Figure 3. The results show a wide range in the number of elements. Nearly 40% of games include 3 or fewer game elements. These are often apps that incorporate game elements like Goals, Challenges, Social Influences, Competition and Real-life incentives in gamification settings rather than as a full game context. Apps like bfit-Smart [58] and Walk With Friends! [30] fall under this distribution. In contrast, almost a quarter of the games include 7 or more game elements. These are often stand-alone games, such as in Garfield Fit! [45] which has characters, costumes and in-game marketplace which needs real steps to buy items from. Another example is Pocket Plants [50] where you grow virtual plants, manage their evolution, interact with non-player characters and use game mechanics like powerups.

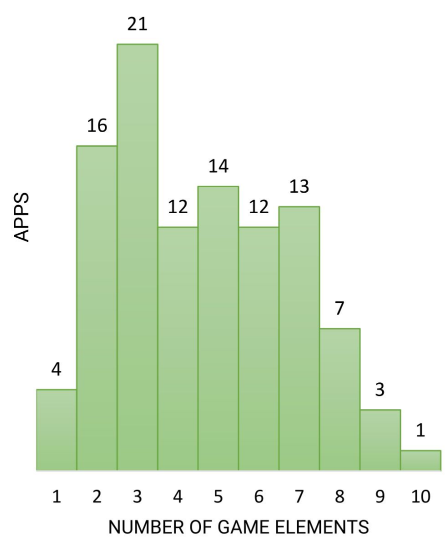

Figure 3: Frequency of apps with the specified number of game elements

The frequency of game elements are shown in Table 2, along with other descriptive statistics. The most common elements such as

Goals (e.g., daily step count), Social Influence (e.g., leaderboard), and Challenges (e.g., Weekend Warrior competitive challenge) relate directly to step tracking and are typically implemented in a gamification style, rather than as standalone games. Other elements that are common in non-fitness-tracker games, such as Collaboration, Unlockable Content, Plot, and Lifelines were far less frequent.

Table 2 also shows information about the quality and popularity of games that contain each game element. Note that data about each game is distributed across all of the game elements that the game includes. Thus, statistical comparisons, which assume independence, are not appropriate to apply. However, the numbers do give a sense of some key differences and similarities among games that include certain elements.

Average ratings are used to estimate quality. Averages were calculated for iOS and Android independently and then a weighted average of the two was calculated based on the number of reviews on each platform. Additionally, any apps that did not have a combined total of at least 30 reviews were excluded from the rating average. The data show little difference in average ratings for game elements, with Badges and Plot at the high end (4.28 and 4.26) and Collaboration and Points at the low end (3.85 and 3.93). However, there is much more variation in the rating standard deviation. This is likely at least in part due to the differences in the number of apps counted in each category since the least common game elements have the lowest standard deviation.

The total number of reviews, which serves as a proxy for popularity, and the median number of reviews are also presented. We used the median, because it is a more meaningful statistic for the skewed distribution. Here we do see some interesting differences. Games with Badges and Real-life Incentives have the highest Median number of reviews, while Plot and Collaboration have the lowest. Combined together with the rating information, it is interesting to note that apps with a Plot are relatively few in number, and less popular, but rated highly. Games with a Collaboration game element are also unpopular, but they also are the least enjoyable. We hypothesize on reasons for this in the Discussion section.

Finally, the average number of game elements that appear in each app with the specified game element are shown. The number of game elements can be thought of as an approximation of the complexity of the gameplay available in the app. We created Figure 4 to better visualize the relationship between the variables in Table 2. The figure illustrates, for example, that games with Real-life Incentives and Goals, typically do not share many other game elements. In contrast, games with Levels, Badges, and Plots often include many other game elements.

4.3 Game Element Co-Occurrences

This section examines the relationships between game elements to better understand how they cluster together in games. We have performed several complementary network analysis and visualization techniques. In each of these, nodes represent individual game elements and weighted edges represent games that use both game elements. Figure 5 shows the complete network with each game element sized by its number of occurrences and edge thickness and opacity mapped to the number of games that include both of the game elements.

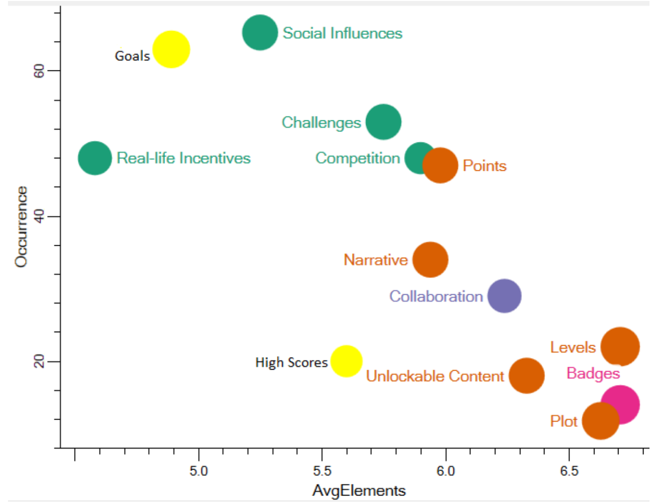

Figure 4: Game elements plotted based on occurrences and average co-occurring elements. Color indicates clusters as described in Section 4.3.

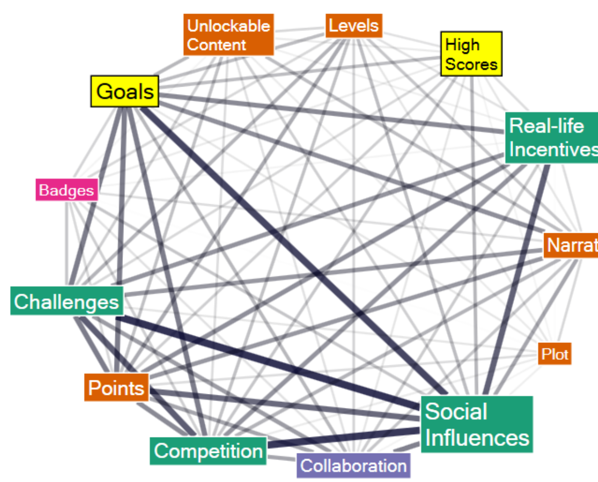

Figure 5: Network Diagram of Game Elements. Size of vertices represent frequency of game elements and edge widths represent co-occurrence between game elements. Color indicates cluster.

As described in the methods section, we applied the Louvain community detection algorithm, which uses the weighted edges to determine which nodes cluster together into distinct sub-networks. The resulting five clusters are color-coded in the network graphs (see Figures 5 & 6). Note that individual games do not fall into one cluster. Instead, these clusters represent game elements that seem to show up together quite often. However, there are often "canonical games" that represent some of these clusters well because they include the key game elements. Below we describe the three clusters that include more than one node and provide some game examples that illustrate these clusters.

One significant cluster formed around Social Influences, Challenges, Competitions, and Real-Life Incentives (see Figure 6). This cluster includes games like Lympo [37] and Yodo - Cash for walking & running (see Figure 7) [62] that allow people to receive real-world rewards for their steps, as well as other gamified apps such as Challenges - Compete, Get Fit [21] and Stroll - Walking Tracker [63] that allow people to compete with their peers in relatively straightforward challenges such as who walks the most or who completes a virtual route first. It includes the most common triad in the network: Challenges, Competition, and Social Influence ($n = 32$), as well as Real-Life Incentives, which is less common, but nearly always connected to those three other game elements. The Goals game element often shows up with these elements (see the thick lines in Figure 5), but because it connected strongly with the High Score element that rarely connects to anything else, the algorithm placed these two in their own cluster.

At the other extreme, is the cluster that includes Narrative, Plot, Unlockable Content, Points, and Levels. Canonical games that have elements in this cluster are stand-alone games rather than gamified apps. For example, in Fitness RPG (see Figure 10) [49], the plot revolves around managing a team of heroes and it utilizes game elements like Unlockable Content and Points in the context of that plot. Some other notable examples include Zombies Run! [52], StepGod [9] and The Walk: Fitness Tracker Game [51].

The Collaboration and Badges single-node clusters appear because the game element (e.g., Collaboration) connects equally to other clusters, making it impossible to place into a single cluster. They can, thus, be interpreted as game elements that are important to several sub-genres of fitness games.

One problem with visualizing the raw network data as shown in Figure 5 is that the popularity of game elements can overshadow the relative importance of connections. For example, there is a very thin edge (weight=15) connecting Social Influence and High Scores. Viewed from the perspective of Social Influence, the edge appears to be a weak connection. However, viewed from the perspective of High Scores, it is among the strongest connections. To account for this, we have created Figure 6, which shows a weighted network graph of game elements based on their co-occurrence and "strength" of their connection with other game elements. This "strength" is represented by edge weight in the figure and represents the percent of games that included both game elements compared to the number of games with a particular element. For example, Narrative shows up in 34 games and Goals show up in 63 games, while they both show up together in 24 games. In this case, the edge "strength" is calculated as:

$$strength = 100 * Max\left(\frac{24}{34}, \frac{24}{63}\right)$$

where $\frac{24}{34}$ is the fraction of Narrative games that also include Goals and $\frac{24}{63}$ is the fraction of Goals games that also include Narrative. We calculate both and then take the maximum value to ensure that if the relationship is "strong" for one of game elements, it will be shown in the graph. We then filter out any edges with a strength of less than 65%. In other words, we only show edges where 65% or more of the game element's occurrences happen with the element it is connected to. This method was inspired from a similar analysis described by [25].

Figure 6 shows several interesting things. Social Influences is not only the most common game element, it is also connected to every cluster identified by the Louvain algorithm. This emphasizes the central role of social features in nearly every type of gamified fitness tracker app. Challenges, Collaboration, and Competition are also connected with many other other game elements, most of which fit with gamified apps, as opposed to standalone games. In contrast, Real-Life Incentives is the only game element with a single connection. Some of the other connections reinforce the Louvain clustering algorithm findings, such as the connection between Goals and High Scores, or the looser, but still connected Levels, Points, Plot, Narrative, and Unlockable Content cluster. The findings from both graphs indicate that these elements often show up together, but not all in the same games, suggesting more diversity in game elements among the relatively small sample of games that use these less popular elements.

5 DISCUSSION

As new technologies are adopted, they inevitably lead to new forms of play. With the widespread adoption of fitness trackers, coupled with mobile devices, a new gaming platform has emerged. This paper is a first step at understanding the ways that game elements have been incorporated into fitness tracker apps. Our hope is that it will serve as a baseline and launching off point for a variety of new studies that can help us understand and better design compelling fitness tracker games or gamified apps.

Future work can now trace the evolution of game elements over time, to identify emerging game genres in this space. For example, this paper identified a popular type of gamified fitness tracker app focused on extrinsic rewards through the use of the Real-life Incentives game element (e.g., Charity Miles [10], Sweatcoin Pays You to Get Fit [55], and Yodo Cash for Running [62]). We showed that these games are quite common, include relatively few other game elements, and are strongly connected to the Social Influence game element. These games show up all along the popularity spectrum, including three of which appear in the top 10 gamified fitness tracker apps. Replication of this work in future years will help identify long-term trends and other emergent game genres in the fitness tracker space.

We also hope that researchers will utilize our results to help them sample fitness tracker apps for more targeted, in-depth qualitative analyses. The full dataset of labeled apps has been made available to support this type of research [43]. For example, a future study could qualitatively examine the 29 apps (28% of reviewed apps) that include the Collaboration game element, in which players work together towards a common goal or objective in the game. The study may help us understand why these games had the lowest average rating and were relatively unpopular (as measured by number of reviews). Perhaps it is related to the inherent difficulty of collaborating with others who have different schedules (e.g., see [6]), since fitness tracking apps are typically played continuously throughout the day. Or it may be technical failures, poor design implementation, or other factors. To address questions like these, researchers can now have a starting point for which apps to include, helping reduce the labor-intensive, yet critical task of systematically identifying such apps.

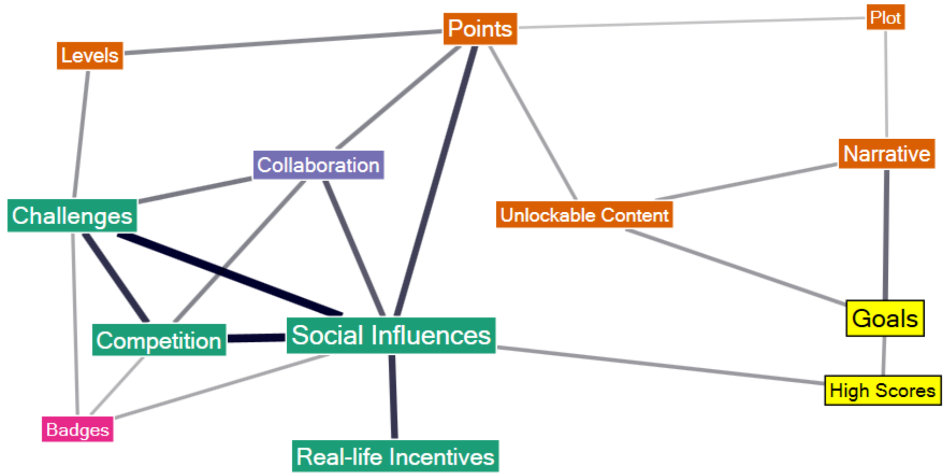

Figure 6: Co-occurence network pattern of game elements. Edge width represent co-occurence weighted by their "strength" which is explained in the referencing section.

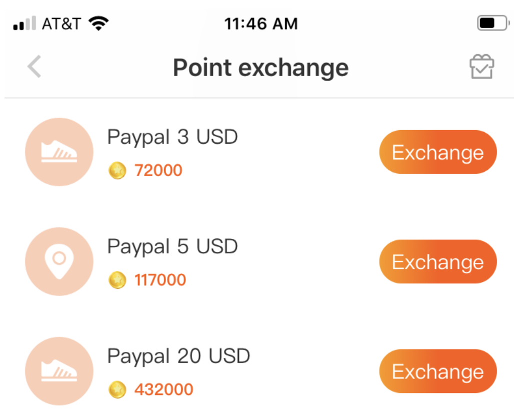

Figure 7: Screenshot of Real-life incentives in the Yodo - Cash for walking & running app [62] where users can exchange points they earn from walking into Paypal transfers. Image ©Yodo Apps.

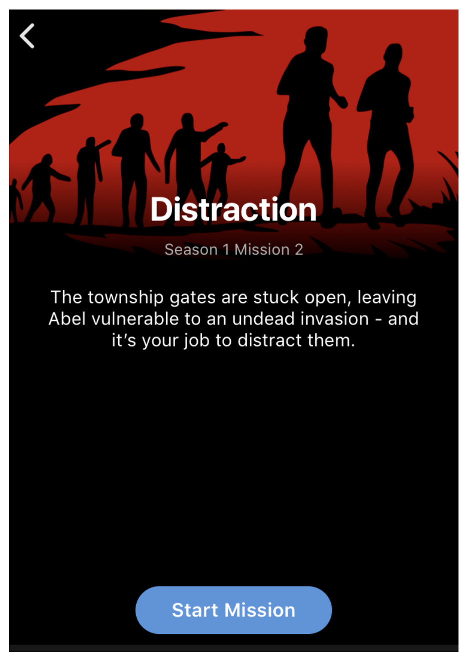

Figure 8: Screenshot of a mission description in the Zombies Run! app [52]. This app can be considered as a full game due to its rich usage of game elements like plot. Image ©Six To Start.

We believe the resulting dataset from this research will also be helpful for app designers to tackle design challenges that arise when developing gamified fitness tracker apps. Our study found that Social Influences plays a central role in many of the apps however there are pros and cons to social facilitation elements. For e.g., social comparison can lead to reduced motivation [11] and sharing personal information can lead to privacy concerns [57]. Yet, many games are fun and engaging precisely because they have a social element. Managing this tension is important for gamified fitness tracker app designers and they can reference our dataset to see how existing apps are managing this tension.

As game designers ourselves, we are also anxious to see this work help identify gaps in the current design space that may be ripe for innovation. Some areas of the design space seem to be frankly, a bit over-saturated. Perhaps because of the goal-oriented nature of walking, over half of fitness tracker apps incorporate Goals, often in a social and competitive context. These are often incorporated into gamified step-count apps, such as Mi Fit [4] and VeryfitPro [53]. Even apps such as Fitbit [20], which incorporate a significant number of game elements, typically have relatively simple game mechanics such as their "who walked the most" challenges. In contrast, plot-driven games, of which there are only 8 (7.7%), are

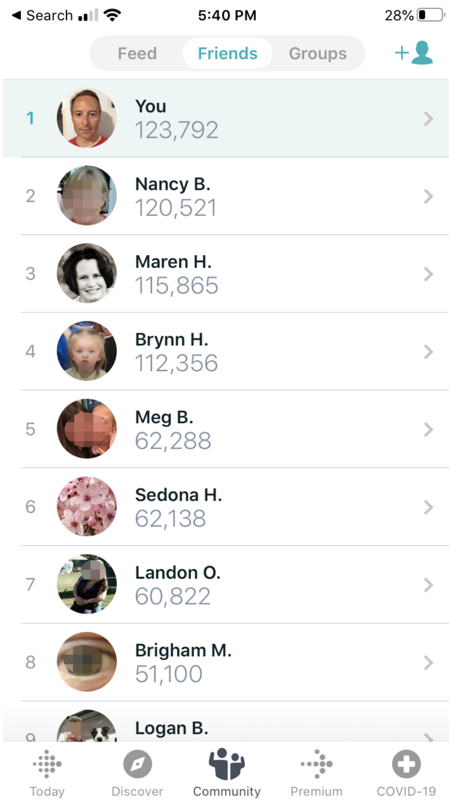

Figure 9: Screenshot of social leaderboard taken from the official Fitbit app [20]. Image ©Fitbit Inc.

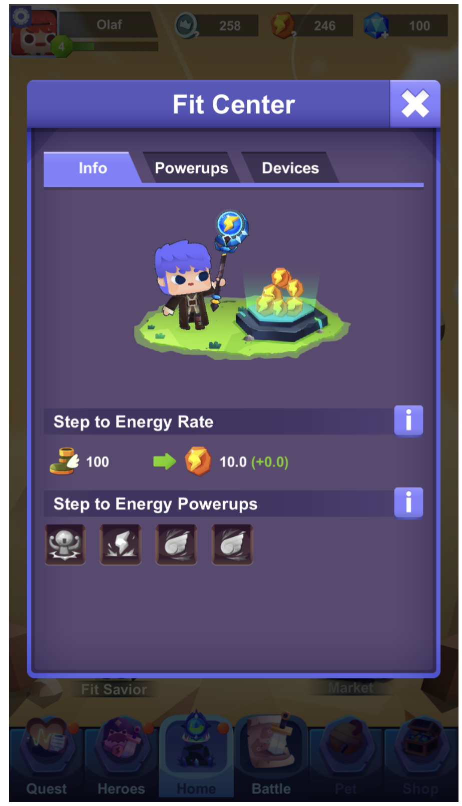

Figure 10: Screenshot from the Fitness RPG app [49]. This app is an example of a canonical game that utilizes step tracking. Image ©Shikudo.

ripe for future innovation. Popular games with the Plot element, such as Zombies, Run! [52] illustrate the viability of games that incorporate stories. But games that include Plot and Collaboration are nearly non-existent (see Space Cupcake [60] for an interesting counter-example). This is in spite of the fact that this combination is so central to other pervasive games such as Alternate Reality Games [8]. Games that allow players to collaboratively take virtual journeys that contain plot elements also seem particularly ripe for innovation. We hope other designers will see different gaps in the design space outlined in this paper and help explore them through novel game designs and research.

Although we believe the contribution of this paper is an important one, it does suffer from several limitations. There are many different taxonomies of game elements and levels of granularity that could have been used. Our approach provides a high-level view of the design space, but it does not delve deeply into the nuanced ways in which the game elements are implemented. Also, due to the nature of our review, this study doesn't evaluate how different game elements meet self-reflection needs of users which is an important consideration for quantified self and long-term activity tracking. [34, 56]. As mentioned before, we hope others will continue this conversation and use this macro view to know where to navigate in more in-depth qualitative game reviews. Another limitation is that, while our review was very systematic, we can't be 100% confident that we have captured every game that uses step-count data. Some games such as Pokemon Go [44] are not included in our dataset, since we focused on fitness tracker (and step-counter) based games rather than location-based games or games that track distance through GPS. Similarly, apps that use other sensors (e.g. GPS, heart rate) could be beneficial in future explorations. Additional work may want to expand on our set of games. Finally, this work only captures a single snapshot in time. Games change and it is likely that new features and game elements will be added to the games we list.

6 CONCLUSION

Fitness tracker data provides a fascinating new platform on which games and gamified apps can rely. This paper characterizes over 100 games selected during our systematic review of step counter mobile games by identifying which of 13 game elements are used in each game. Over 100 fitness tracker apps identified include at least one game element, and the majority of the apps include several game elements. This paper also helps visualize the design space by mapping out which game elements cluster together and which rarely show up together. The evidence suggests that there are significant opportunities for novel step-counter games that blend together game mechanics in interesting and fun ways, rather than simply relying upon standard gamification elements and leaderboards.

Game	Game Elements	Installs (Android)	Last Updated (Android)	Last Updated (iOS)	Reviews	Weighted Avg. Rating
Mi Fit	2	50,000,000	13	22	937,981	4.5
Pacer Pedometer - Step Tracker	6	10,000,000	5	12	802,561	4.7
Fitbit	6	10,000,000	6	7	712,425	3.8
Sweatcoin Pays You To Get Fit	3	10,000,000	10	4	276,360	4.3
Walkr: Fitness Space Adventure	5	500,000	17	19	67,764	4.4
Charity Miles	2	500,000	14	32	55,603	4.6
VeryfitPro	1	5,000,000	6	40	48,160	3.1
Fit the Fat 2	4	5,000,000	300	300	47,116	3.7
Yodo Cash for Running	6	1,000,000	58	N/A	38,919	4.1
Zombies, Run!	7	1,000,000	19	9	33,708	4.5
Achievement - Reward Health	2	500,000	50	69	30,008	4.7
Runtopia Pays You To Get Fit	3	1,000,000	54	54	29,728	4.4
Pocket Plants	7	500,000	4	7	27,426	4.4
StepBet: Get Active & Stay Fit	5	100,000	58	21	14,037	4.7
Winwalk pedometer	2	500,000	54	N/A	11,661	4.1
Thunderpod - The fitness game	7	100,000	9	6	10,295	4.2
Wokamon - Monster Walk Quest	5	100,000	40	27	9,862	4.2
Lifecoin	3	100,000	N/A	449	9,686	4.5
FeetApart - Walk and Earn Rewards	3	100,000	33	38	6,829	3.6
Pact: Earn Cash for Exercising	2	500,000	1035	N/A	5,579	2.4
Fitness RPG - Gamify Your Pedometer	7	100,000	37	60	4,445	4.3
Lympo - Get Money for Walking	4	100,000	7	7	4,307	3.5
Carrot Rewards	4	500,000	313	N/A	3,981	2.4
Walkingspree	7	10,000	26	23	3,593	4.6
One You Active 10 Walking Tracker	4	100,000	76	42	3,136	4.2
Color Band A1	1	500,000	345	N/A	2,836	3.8
Walk for a Dog	7	100,000	6	68	2,685	3.2
i-gotU Life	4	100,000	75	71	2,328	3.7
Challenges - Compete, Get Fit	8	N/A	N/A	7	2,300	4.6
SquadEasy	9	10,000	15	105	1,982	4.1
Unicef Kid Power	7	100,000	28	33	1,793	4.0
Yes.Fit	6	50,000	6	8	1,444	4.4
Carrot Wellness	6	10,000	936	462	1,372	4.2
Earthmiles	4	50,000	93	461	1,166	3.7
Burn to Give	3	100,000	14	18	787	4.2
Garfield Fit	6	100,000	972	967	735	3.6
My Virtual Mission	4	10,000	129	395	656	4.3
Social Steps	6	N/A	N/A	41	637	4.6
The Walk: Fitness Tracker Game	7	10,000	68	64	627	4.0
Paidtogo - Walk, Run and Earn	5	N/A	N/A	5	622	4.5
HealthCoin	3	100,000	184	180	547	3.2
Munzee	9	1,000	8	8	389	3.6
Runbet	3	10,000	581	581	369	3.7

Table 3: The most popular fitness tracker game apps sorted by number of app reviews on both Google Play Store and Apple App Store. The weighted average rating is weighted based on the number of reviews in each Store. Last updated values represent the difference in days between April 21, 2020 (when the data was captured) and the date the app was last updated. Note that some apps are not available on both platforms.

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