Successfully developing a physical activity or exercising habit is often hard to achieve. When a decision to take up active behavior has been made and 'first steps' have been taken, the hardest part, maintaining this behavior over time, is still to come. Wearable technology has promising potential to keep people motivated but in reality, they are often as quickly abandoned as they have been adopted.

This dissertation argues that the data produced by these wearables is not adequately translated into a motivating environment. Too often do platforms 'isolate' the wearable user with their personal data, focusing too much on self-regulatory features. Relying on Self-Determination Theory, this dissertation argues that to motivate the user, wearable data should be provided in a social and engaging environment, where social interaction and gamification features take up a prominent role.

Four studies, focusing on the role of social interaction in existing Online Fitness Communities, were conducted to test this hypothesis. Results indicate that social interaction and gamification features have significant potential to improve the motivational potential of data analysis platforms and as such, better assist people in keeping up their healthy behavior.

Physical Activity
in the Digital Age

An Empirical Investigation into the Motivational Affordances of Online Fitness Communities

Jeroen Stragier

UNIVERSITEIT
GENT

Jeroen Stragier
Physical Activity in the Digital Age

Physical Activity in the Digital Age: An Empirical Investigation into the Motivational Affordances of Online Fitness Communities

Jeroen Stragier

Proefschrift voorgedragen tot het behalen van de graad Doctor in de Communicatiewetenschappen
Academiejaar 2016-2017

Stragier, J. (2017). Physical Activity in the Digital Age. An Empirical Investigation into the Motivational Affordances of Online Fitness Communities. Ghent University: Faculty of Political and Social Sciences, Department of Communication Studies, IMEC-MICT, Ghent, Belgium.

Promotor: Prof. Dr. Lieven De Marez

Copromotor: Prof. Dr. Mariek Vanden Abeele

Print: University Press

Samenstelling examencommissie:

Promotoren: Prof. Dr. Lieven De Marez

- Universiteit Gent

Prof. Dr. Mariek Vanden Abeele

- Tilburg University

Voorzitter: Prof. Dr. Gino Verleye

- Universiteit Gent

Leden: Prof. Dr. Greet Cardon

- Universiteit Gent

Prof. Dr. Steven Vos

- Technische Universiteit Eindhoven, Fontys Sporthogeschool

Prof. Dr. Koen Ponnet

- Universiteit Gent

Dr. Peter Mechant

- Universiteit Gent

Dankwoord

Mijn doctoraat is af. De laatste maanden waren heel intens, maar het resultaat mag er zijn en ik ben dan ook heel tevreden. Het is gegroeid uit mijn passie voor sport en bewegen en mijn ongebreidelde interesse voor draagbare sensoren en technologie die ons in staat stellen om onszelf te kwantificeren. Het resultaat, dat ons moet in staat stellen om deze technologie verder te ontwikkelen en in te zetten om meer mensen aan het bewegen te krijgen, is dan ook wat ik bij het begin voorgesteld had. Dat begin ligt ondertussen een viertal jaar achter ons, toen ik eigenlijk van plan was om een doctoraatsbeurs op te nemen bij de bewegingswetenschappen. Lieven slaagde er uiteindelijk in om mij te overtuigen om te blijven en een doctoraat aan te vatten dat twee werelden, nieuwe mediastudies en bewegingswetenschappen zou combineren. Lieven, bedankt om mij deze kans te geven en Greet, ook jij bedankt om in de loop der jaren de samenwerking tussen onze vakgroepen aan te halen. Nu het bedanken begonnen is, wil ik zeker twee mensen vermelden die heel belangrijk geweest zijn bij het vormgeven van dit doctoraat: Peter en Mariek. Bedankt Peter, de dataverzameling van dit doctoraat zou er volledig anders uitgezien hebben zonder jouw excellente kennis van digital methods, API's en webscraping. Bedankt Mariek, voor het helpen vormgeven van de theoretische onderbouw van dit doctoraat, voor het nalezen, comments geven… Ik ben er zeker van dat jouw hand het werk beter gemaakt heeft. Bedankt ook aan mijn doctoraatsjury, voor jullie bereidheid om mijn werk te evalueren.

Een doctoraat schrijf je natuurlijk niet alleen op het werk. Het begint met het krijgen van kansen, te beginnen met deze die ik kreeg van mijn ouders. Ik ben heel dankbaar dat ik altijd mijn eigen studiekeuzes heb mogen maken en ben blij dat die keuzes nu ook tot dit resultaat hebben geleid. Bedankt ook aan de rest van de familie, voor de gezellige band die we met elkaar hebben en Jasper voor de geslaagde cover. Bedankt Wevelgemse vrienden, voor de vele leuke uren in den Alfa, de Polka, de Chiro, het tsjolen, de minivoetbal, de festivals, de reizen… Ik hoop dat we als groep nog lang zo sterk mogen samenhangen. Het triatlon- en duatlonwereldje heeft hier ook wel een plaatsje, als uitlaatklep en bron van inspiratie & motivatie de afgelopen vier jaar. De collega's bij MICT en de vakgroep mag ik zeker niet vergeten, voor de collegiale sfeer, het enthousiasme en de legendarische teambuildings.

Tenslotte wil ik Ellen en Winter, mijn twee grootste schatten, bedanken. Jullie enthousiasme en liefde zorgen ervoor dat het altijd een plezier is om thuis te komen.

Gent, April 2017,

Jeroen Stragier

Nederlandstalige samenvatting

In dit proefschrift wordt vertrokken van een aantal observaties in de hedendaagse samenleving. Ten eerste kampt een belangrijk en toenemend deel van onze bevolking met overgewicht. Mensen met overgewicht lopen een verhoogd risico op het krijgen van diverse levensstijl-gerelateerde aandoeningen zoals diabetes type 2, hart- en vaatziekten, mechanische problemen in knieën, heupen en rug en mentale problemen. De bijhorende kosten voor de publieke gezondheidszorg kunnen hierbij niet worden verwaarloosd. Gebrek aan lichaamsbeweging is één van de belangrijkste oorzaken, en bijgevolg zijn initiatieven ter bevordering van lichaamsbeweging broodnodig. Ten tweede kennen draagbare technologieën, de zogenaamde 'wearable tech', op dit moment een sterke ontwikkeling, en dit in het bijzonder in de medische en gezondheidssector. Deze technologieën geven mensen een gedetailleerd inzicht in verschillende aspecten van hun gezondheid, onder andere door het meten van dagelijkse fysieke activiteit in termen van bv. slaapkwaliteit, verbruikte calorieën of het aantal gezette stappen. Daarnaast kunnen ze bijvoorbeeld nog meer gedetailleerde informatie geven over parameters met betrekking tot loop- en fietsactiviteiten zoals locatie, afgelegde afstand en snelheid. De combinatie van een gebrek aan lichaamsbeweging enerzijds, en het voorhanden zijn van draagbare technologieën anderzijds, maakt dat we ons de vraag kunnen stellen of deze technologieën een ondersteunende rol kunnen spelen in het motiveren van hun gebruikers om fysiek actief te zijn/blijven.

Bijzonder relevante technologieën in dit licht, zijn fitness trackers (meestal onder de vorm van een polsband) en geavanceerde (smart) sporthorloges. Deze technologieën, die parameters met betrekking tot wandel-, loop- en fietsactiviteiten zoals locatie, afgelegde afstand en snelheid meten, kennen op dit moment een groeiende adoptie. Deze toenemende adoptie wordt gevoed door een maatschappelijke trend naar gezonder leven, die onder andere waarneembaar is in de groeiende populariteit van bv. (gezonde) voedingsblogs op sociale media en de groei van (recreatief) hardlopen en fietsen in Vlaanderen. Hoewel technologie mensen kan voorzien van een middel om hun gezondheid meer in eigen handen te nemen, toont onderzoek aan dat adoptie niet automatisch leidt tot langdurig gebruik van de technologie en als dusdanig ook niet automatisch leidt tot de beoogde continuering van fysieke activiteit. Dit probleem dwingt ons bijgevolg om kritisch te kijken naar de factoren die al dan niet bijdragen tot het (blijvend) gebruik van deze technologieën in de ondersteuning van beweeggedrag, aangezien enkel inzicht in deze factoren ertoe kan leiden dat we technologieën met meer succes kunnen inzetten.

Dit proefschrift situeert zich tegen de achtergrond van bovenstaand probleem. Het proefschrift vertrekt van de observatie dat de data verzameld door fitness trackers en sporthorloges gewoonlijk toegankelijk zijn voor de gebruiker via (online) platformen waarop de data die worden verzameld, gepresenteerd en geanalyseerd worden. Deze online platformen worden doorgaans aangeboden door de producenten van fitness trackers en horloges, en worden *‘brand-based’ platformen* genoemd in dit proefschrift. In dit proefschrift vertrekken we vanuit de assumptie dat zulke brand-based platformen de gebruiker niet adequaat motiveren om te (blijven) bewegen. We baseren ons hiervoor op de Zelfbeschikkingstheorie voor motivatie (ZBT). Op basis van deze theorie, stellen we dat de meeste van deze ‘brand-based’ platformen te zeer gefocust zijn op het proberen verhogen van het gevoel van ‘competentie’ en ‘autonomie’ bij de gebruiker, en te weinig op het verhogen van het gevoel van ‘verbondenheid’, dat de gebruiker zou moeten ervaren door samen met anderen te bewegen. Dit komt omdat op ‘brand-based’ platformen voornamelijk ‘zelfregulatie’ features aangeboden worden die de gebruiker in staat stellen om zijn/haar gedrag te monitoren en bv. toe te werken naar specifieke en/of zelf gestelde (bewegings)doelen. Het is één van de uitgangspunten van dit proefschrift dat dit soort 'geïsoleerde' omgeving, waarin een persoon 'in quarantaine' geplaatst wordt met zijn/haar data niet de juiste manier is om hem/haar te motiveren om voldoende te bewegen en dit op de langere termijn ook vol te houden.

Om deze assumptie te staven richten we ons in dit proefschrift op de affordances van *Online Fitness Communities* (OFC). Deze online platformen zijn gelijkaardig aan de zogenaamde ‘brand-based’ platformen, vooral wat betreft het aanbieden van ‘zelfregulatie’ features. Toch is hun insteek enigszins anders. In vergelijking met ‘brand-based’ platformen, zijn ze veel sterker gericht op het creëren van een online community rond ‘bewegen’. Het meest succesvolle voorbeeld van deze 'community-benadering' is 'Strava', maar ook andere platformen zoals ‘RunKeeper’ en ‘MyFitnessPal’ hebben een grote, actieve en groeiende gebruikersgroep. Op basis van de inzichten uit de ZBT alsook uit andere communicatiewetenschappelijke en bewegingswetenschappelijke theorieën, veronderstellen we in dit proefschrift dan ook dat online interactie in OFCs met betrekking tot fysieke activiteit mensen een gevoel van verbondenheid laat ervaren met andere community-leden en leidt tot het krijgen en geven van erkenning en sociale steun voor geleverde prestaties of activiteiten. Deze erkenning en steun kunnen als cruciaal worden beschouwd voor het duurzaam gebruiken van de OFC.

Kortom, we verwachten dat data-analyse platformen succesvoller kunnen zijn bij het motiveren van mensen om te blijven bewegen wanneer naast 'zelfregulatie' features ook sociale features aangeboden worden aan de gebruiker. Het doel van dit proefschrift is dan ook de *ontwikkeling en empirische toetsing van een theoretisch model waarin de motivaties voor (langdurig) gebruik van OFCs worden blootgelegd.*

Voor de toetsing van dit theoretisch model werden vier studies uitgevoerd, ieder met een sterke focus op de rol van sociale affordances van OFCs. In studies 1 en 2 werd aangetoond dat sociale interactie-features sterk geapprecieerd worden door gebruikers. Het gebruik van deze features leidt tot interacties tussen gebruikers waarbij men elkaar steunt en erkenning geeft voor zijn/haar beweeggedrag, zowel binnen de OFC als op reguliere sociale netwerksites (zoals Facebook). In de derde studie worden de verschillende types van motivaties om te bewegen gelinkt aan de waargenomen affordances van OFCs en wordt aangetoond dat OFC features anders gebruikt worden naargelang de verschillende motivaties die men heeft om te bewegen. In de vierde studie, ten slotte, werd gekeken in welke mate sociale affordances een belangrijke rol spelen bij langdurig gebruik van OFCs. De studie toont aan dat OFCs initieel vooral gebruikt worden omwille van hun zelfregulatie-features, maar dat het gebruik van sociale features na verloop van tijd toeneemt en belangrijker wordt voor het integreren van OFC gebruik in het beweeggedrag. Dit toont het potentieel aan van sociale interactie-features om een platform aantrekkelijk te maken en de gebruikers ervan geëngageerd te houden.

Op basis van de resultaten van deze studies werd het initieel opgestelde theoretische model verfijnd en op enkele punten herwerkt. Kwantificatie van (beweeg)gedrag via draagbare technologie vormt de basis van het model en levert de input voor drie feature categorieën: zelfregulatie-, sociale interactie- en gamification-features. Volgens het model worden door de combinatie van deze drie categorieën de basisbehoeften 'autonomie', 'competentie' en 'verbondenheid' beter aangesproken dan het geval is in veel van de bestaande data-analyse platformen of interventies, die vooral gericht zijn op zelfregulatie. Het model geeft aan hoe technologie (beter) kan ontwikkeld om een hoger engagement bij de gebruiker te verkrijgen en hen zo beter te ondersteunen in hun poging om meer te bewegen. Het uiteindelijke model moedigt toekomstige wetenschappers in dit domein aan om het gebruik van wearables, fitness trackers en OFCs te bestuderen vanuit een motivationeel perspectief. De inzichten uit het model kunnen eveneens bijdragen aan het ontwikkelen van toekomstige iteraties van deze technologieën.

English summary

This dissertation departs from a number of observations in contemporary society. First, a significant proportion of the population in our society is overweight and this number is increasing. Overweight people are at risk of various lifestyle related health conditions such as Type 2 diabetes, cardiovascular diseases, mechanical issues in knees, hips and back and mental issues. The associated cost to public healthcare cannot be neglected. Lack of physical activity is one of the leading causes of overweight. Consequently, it is crucial to invest in efforts to increase physical activity in the general population. Second, technological advances in our society are driving the development of wearable technology, especially in healthcare, medical and fitness contexts. These technologies provide people with detailed information about various aspects of their health, among others by registering users' daily physical activity in terms of for example step counts, calories or by providing detailed information about exercise parameters. Wearable (wrist-based) fitness trackers and advanced (smart) sports watches measuring these parameters are experiencing rapid adoption at the time of writing. The success of these technologies is fueled by a societal trend towards healthier living, observable in the growing popularity of (healthy) nutrition blogs on social media and the growth of recreational running and cycling participation. However, while these technological developments can provide citizens with a means to take their health into their own hands, research indicates that the uptake of these technologies does not result in sustained usage and as such, may not lead to the aspired maintenance of physical activity. This problem forces us to look closely at the factors that may contribute to or hinder the sustained use of these technologies. After all, only when we gather insight into these factors, will we be able to successfully implement them.

This dissertation situates itself against the backdrop of the aforementioned problem statement. It departs from the observation that the data that is collected with wearables is oftentimes made accessible to most users through (online) platforms on which the collected data are presented and analyzed. These platforms are usually provided by wearable producers of fitness trackers and sports watches, and will be termed *brand-based platforms* in this

dissertation. A core assumption of this dissertation is that these brand-based platforms do not adequately address the user's motivation to stay physically active. Relying on Self-Determination theory (SDT), we argue that most of these brand-based platforms focus too strongly on attempting to enhance the user's sense of competence and autonomy, two of the three basic needs underlying one's motivation for engaging in certain behavior, while neglecting the third, the need for belonging and relatedness of the user. They do this by offering the user mainly self-regulatory features, which allow them to self-monitor their behavior and work towards specific or self-set goals, using their personal data collected with a wearable. It is one of the basic assumptions of this dissertation that this type of 'isolated' environment, in which a person is 'quarantined' from others with his data, does not deliver the best results at motivating him/her in keeping up healthy behavior or exercising.

To substantiate this claim, this dissertation focuses on the affordances of so-called *Online Fitness Communities* (OFCs). These online platforms are similar to the brand-based platforms cited above, as they offer similar self-regulatory features. Their approach is somewhat different, however, as they also focus strongly on letting their users experience their exercise behavior in connection with online peers in a virtual community environment. The most successful example of this 'community approach' is the OFC 'Strava', but other OFCs such as RunKeeper and MyFitnessPal also have large, active and growing user bases. Based on the insights from SDT and other theories in the fields of communication and movement sciences, we assume that the online interaction around exercise behavior in these OFCs lets people experience a sense of belonging and relatedness to other community members and delivers them recognition and online social support for their exercise behavior. This recognition and support can be considered as crucial for the sustained use of the OFC.

In short, we expect that data analysis platforms could be more successful at motivating users to stay physically active when they offer their them features that enable both self-regulatory and social affordances. Hence, the objective of this doctoral thesis *is to develop a research-based framework that unravels the underlying reasons for continued OFC use.*

To empirically validate our theoretical framework, four studies were conducted focusing on the role of the social affordances of OFCs. In studies 1 and 2, we demonstrated that social interaction features are used and appreciated by OFC users. Their use results in users supporting and endorsing each other for their activities, both in the OFC community as on other, mainstream social network sites (for example, Facebook). The third study connects motivations for being active with perceived affordances of OFCs and demonstrated that OFC features are used differently in accordance with a person's motivations to exercise. Lastly, our fourth study assessed whether social affordances can play a role in creating sustained OFC use. The study illustrates how OFC use shifts from being self-regulation centered in the beginning to more socially oriented in the longer term, indicating the potential of social interaction features to keep a platform engaging, and thus the user engaged.

Based on the results of these studies, the initial framework was slightly revised. In the final theoretical model, quantification of behavior through wearable technology constitutes the baseline of the model and serves as input to three feature categories: self-regulatory, social interaction and gamification features. According to the model, the combination of these three categories better addresses all three basic psychological needs underlying motivation than many of the existing brand-based platforms or interventions, which mainly focus on self-regulation. As such, the model demonstrates how technology can be used more effectively to motivate people to maintain a healthy lifestyle. The theoretical model encourages researchers in this field to study wearable, fitness tracker or OFC use from a motivational perspective. In addition, the insights can contribute to and therefore guide the future development of these technologies.

Table of Contents

INTRODUCTION

New media technologies have become prominent actors in our daily lives. They have a significant impact on our behavior as they change the way we interact, work, spend our leisure time and consume media (Castells, 2011). One area of life in which this significant impact is noticeable, is that of health & fitness. Indeed, technology plays to an increasing degree its role in supporting our health related behaviors. The rapid growth of the fitness & health wearable market can be regarded as a core indicator of the increased importance of technology for health and fitness.

The promise of fitness and health wearables is to make and keep people fit (again), thereby aiding them to lead live healthier lives (for example www.fitbit.com). The primary means via which they aim to achieve this, is by providing the user with large amounts of personal data, also referred to as personal informatics (Epstein, Ping, Fogarty, & Munson, 2015). At this time, these data primarily concern physical activity related metrics that can be tracked via movement sensors, such as step counts, heart rate and sleep quality.

The process of registering and storing biometric data on one's health and fitness behavior can be considered as a process of *quantification*, whereby users quantify certain bodily characteristics (e.g. weight) or functions (e.g. heart rate) in order to consequently make sense of them (e.g. answering the question how weight and heart rate fluctuate over time). This 'making sense' of data usually occurs via dedicated data analysis platforms which analyze and interpret the data collected by the wearable (e.g. a mobile phone or fitness bracelet) and give feedback to the user. In the context of health and fitness, quantification of the body through sensor technologies and their associated data analysis platforms enables users to register, store and interpret data collected on their own health behavior, without the aid of a third party such as a doctor, fitness trainer or another health professional. As such, the ‘spirit’ of these technologies (cf. DeSanctis & Poole, 1994) is to empower individuals by giving them a means to know their bodies better and make informed decisions on how to live healthier lives (Almeida, 2015; Burns, Lueg, & Berkovsky, 2012).

The wearable market is experiencing considerable growth (3.1% in Q3 2016), with fitness trackers representing 85% of the sales in the market (IDCresearch, 2016). However, in contrast to this market growth, market analysis data is also indicating that a significant part of fitness tracker adopters stops using the device already within 6 months after acquisition (Clawson, Pater, Miller, Mynatt, & Mamykina, 2015; Lazar, Koehler, Tanenbaum, & Nguyen, 2015; Endeavour Partners, 2014). This implies that, to some extent, these devices fail to keep their users engaged. This dissertation argues that the cause of this lack of engagement lies in the affordances of the data analysis platforms that accompany these devices. Some data analysis platforms, which mainly focus on exercise behavior, aim to tackle this lack of engagement by offering features that extend beyond a mere analysis of the personal metrics. These platforms enable users to, for example, connect and share their experiences, activities, pictures and much more with their online peers. Oftentimes they also carry self-regulatory features, such as offering users the opportunity to define certain goals for themselves to reach and gamification features, such as obtaining ‘rewards’ for reaching certain activity thresholds. Since these platforms usually lay a strong focus on the platform as a social network, however, they are often referred to as fitness social networks, social fitness apps or Online Fitness Communities or ‘OFCs’. We will further use the term OFC in this thesis. Popular examples of OFCs are Strava, RunKeeper and Endomondo. Each of these platforms provides the user with feedback about his/her exercise behavior, and simultaneously enables him/her to interact upon these achievements with their (online) peers.

OFCs operate on the basis of users (automatically) registering their exercise behavior. It is only when users (regularly) register their exercise behavior on the platform that they can obtain feedback on their performance, can interact with each other over it, and can be rewarded or challenged over it. Hence, given that users keep the OFC alive by ‘feeding’ it with their activities, OFC use can be considered as a proxy for performing exercise behavior (but not vice versa: people might of course be exercising without using an OFC).

OFCs are experiencing rapidly growing user bases (Sawh, 2016). RunKeeper, for example, saw its user base increase from 2 million users in 2010 to 45 million users in 2016. Similarly, Runtastic is estimated to have 40 million active users and Endomondo has 20 million. Strava is reluctant to share its official user bases. In the recently released country reports however, they state that each second, 9.6 activities were shared on Strava worldwide in 2016. In 2015, this was 5.3 activities, indicating a significant growth of their user base. Given the link between sustained OFC use and sustained exercise behavior, this suggests that these platforms may play a role in supporting people in sustaining their active lifestyle. To date, however, it is unclear to what extent users use the different features present in OFCs, and to what extent this usage leads to sustained OFC use. This is unfortunate. After all, a better understanding of which technological features assist people most effectively people in sustaining their OFC use (and thereby indirectly their exercise behavior), can inform technology developers, policy makers, and health practitioners on how to develop more engaging platforms and interventions.

Hence, the objective of this doctoral thesis is ***to develop a research-based framework that unravels the underlying reasons for continued OFC use.*** To that end, 4 studies have been conducted to determine how self-regulatory and especially social features contribute to a higher platform engagement and persisted use behavior in OFCs. More specifically, we studied how the motivation for exercising of existing OFC users is affected by these features.

If we can gather insight into what aspects of OFC use matter most, these insights might also aid in understanding the user's persistence in use of other types of online communities dedicated to behavior change, such as, for example, online communities to support energy efficiency or greener mobility.

1 CONTEXTUALIZATION

CHAPTER ONE: PHYSICAL ACTIVITY IN A DIGITAL ENVIRONMENT

1. Societal context

Some may argue that wearable technology for health and fitness is just a hype. When looking at the state of health and fitness in the general population, however, it becomes clear that technological support may be more relevant than ever. Indeed, research shows that an increasing proportion of the population in Flanders is overweight. While the average BMI in Flanders in 2008 was 24.6, this number has increased to 25.4[1] in 2013. A balanced diet and sufficient physical activity are necessary conditions to maintain a healthy weight. Physical activity refers to 'any bodily movement produced by skeletal muscles that requires energy expenditure' (WHO, 2015). This implies any movement that causes a person to burn more calories than they would at rest. Moderate-to-vigorous physical activity then (cycling for transportation, for example), is any activity that increases one's heart rate and causes them to be out of breath for some of the time. A healthy adult should perform 30 minutes of moderate-to-vigorous physical activity per day to be in good health and reduce risk for lifestyle related health conditions (Haskell et al., 2007). In Flanders, only 39.7% of the population older than 15 meets this requirement (Gisle & Demarest, 2013). This puts a significant proportion of the population at risk of lifestyle related health conditions such as Type 2 diabetes, cardiovascular diseases, mechanical issues in knees, hips and back and mental issues such as depression and low self-esteem (Garber et al., 2011). Furthermore, treatment of these issues imposes a serious pressure on our healthcare system. In comparison to adults with a normal weight, overweight adults visit the doctor more often, require more prescription drugs and are more frequently hospitalized. Median total healthcare costs per year are significantly higher for overweight persons (Raebel et al., 2004). A focus on prevention of lifestyle related health conditions instead of treatment after onset appears to be necessary in this perspective.

---

[1] Body Mass Index is a measure representing length/the weight ration of a person. A BMI between 18 and 25 is considered to be normal. A BMI higher than 25 is considered an indicator of overweight.

To a certain extent however, a growing trend towards healthier and more active living is emerging (QRI, 2015). This trend is noticeable in for example the emergence of healthy food bars and popularity of (allegedly) ultra-healthy diets as raw food diets, vegetarianism and paleo, but also, in the growth of fitness tracker adoption and in the growing participation in exercising activities as running and cycling (Borgers, Pilgaard, Vanreusel, & Scheerder, 2016). 'Exercising' or exercise behavior is referred to as 'any (moderate-to-vigorous) physical activity that is 'planned, structured, repetitive and purposeful', often performed to improve one's physical fitness (WHO, 2015). Indeed, the advantage of activities as running and cycling is that they can be performed at a moment that suits the runner of cyclist best. Although this implies more solitary exercise behavior, recreational events increasingly succeed in bringing these individuals together. In Flanders, Belgium, recreational events have experienced a significant growth in recent years. In 2016 for example, 39.000 people participated in the Antwerp Ten Miles event, 16.000 recreational cyclists rode the Tour of Flanders for amateurs and start-to-run initiatives by local running teams or cities are also gaining in popularity. These runners and cyclists increasingly use technologies as fitness trackers and smartphone apps to collect data on or 'quantify' their exercise behavior. This quantification of exercise behavior is the behavior of interest to the research conducted in this dissertation and more specifically, what is done with the data once it has been collected.

2. It all starts with quantification…

Wearable technology is a hot topic in the technology landscape at the time of writing (Woods & van der Meulen, 2016). Although often still termed as a 'hype', these 'gadgets' are steadily becoming a substantial market with growing adoption among various population (Endeavour Partners, 2014). In Flanders, Belgium, wearable adoption increased from 7 to 13% (Vanhaelewyn, Pauwels, De Wolf, Accou, & De Marez, 2015, 2016), bringing it close to the point of mass-market entry (Ferguson, 2014; Rogers, 1995).

The term 'wearables' refers to 'computing devices assembled in a way which allow it to be worn or carried on the body while still having the user interface ready for use at all times' (McCann & Bryson, 2009, p. 4). The smartphone, a wearable device in itself, is generally used as an interface to operate these various wearables. The data registered by the sensors in the wearable, then, can be accessed via a dedicated app on the smartphone (or other type of computer). Data transfer between smartphone and wearable is most commonly over Bluetooth Low Energy (BLE), Wi-Fi or 4G. The computational power of smartphones, their broad connectivity options, the fact that people carry them along nearly always, and their large, high definition displays make them an excellent tool for data collection, analysis and visualization (Kas, 2014).

Generally, three categories of wearables can be distinguished on the consumer market: wearables for infotainment, medical & healthcare and fitness & wellness (IHS, 2013). The *infotainment* category includes those wearables developed to support information and entertainment purposes. Popular examples in this category are the much hyped and recently discontinued 'Google Glass' or Microsoft Hololens and more recently, Virtual Reality headsets. Smartwatches can also be placed in this category, although these wearables increasingly show convergence with smart sports watches.

Wearables for *medical & healthcare* are allegedly the most promising market segment (IDTechEx, 2015a, 2015b). Existing wearables in this segment allow patients to, for example, measure and follow up on parameters as blood glucose and blood pressure by themselves. One of the challenges in this market is to offer wearables that allow patients to perform medical tests with medical grade accuracy at a reasonable price (Kas, 2014). The development of this segment is essential in patient empowerment, a key premise of e-&mHealth[2] initiatives.

Finally, wearables for *health & fitness* are currently the largest segment, especially due to the increasing uptake of fitness trackers and activity monitors developed by companies such as Fitbit, Garmin and Polar. Their main purpose is to collect data their user's physical activity

[2] e-&mHealth refers to the application of electronic and mobile communication technology in healthcare to facilitate better and personalized healthcare (Gurman, Rubin, & Roess, 2012; Kay, Santos, & Takane, 2011). WebMD and MayoClinic.com e.g., are examples of how the internet is increasingly used for gathering health-related information and data (in medical circles often referred to as 'Dr. Google'), while platforms as VirtuMedix and eVisit afford physician consultation online. Online communities and forums such as PatientsLikeMe help connect patients with others diagnosed with similar conditions to share treatment experiences and help advance research into their condition. mHealth then, relies more on the use of wearable technology, with smartphone or tablet applications as the primary interface for data visualisation. The widespread adoption of smartphones and the affordances of smartphone applications are driving this trend towards mHealth applications. More specifically, smartphone applications allow us to reach a broader public, while being able to target them more personally and as such achieve better engagement in interventions and a more convenient patient follow-up afterwards (Price et al., 2014). As such, mHealth is applied in the support of both physical as well as mental conditions, across a wide array of target populations. mHealth applications are available for clinical assistance in diagnosis, remote monitoring of patients, reminders for medication intake or appointments and healthy living, (Chouffani, 2011).

throughout the day, such as steps taken, energy expenditure en sedentary behavior. Furthermore, they can be used to log exercise behavior. Smartphones and more expensive sports watches often enable capturing parameters of exercise behavior such as distance covered, speed and more through additional on-board sensors as GPS and optical heart rate monitoring. In the remainder of this thesis, these kinds of health and fitness wearables will be referred to as '**fitness trackers**'.

The above overview demonstrates that wearables are being developed in different market segments. Increasingly, a convergence can be noticed between the three wearable categories described above, a trend that has occurred before for various technologies (Straubhaar, LaRose, & Davenport, 2013). Health and Fitness wearables are currently driving this convergence, in which collecting personal informatics on health is increasingly complemented with for example smart watch function as e-mail alerts. The convergence with medical grade wearables indicates the objective to develop fitness wearables into medical grade devices.

To our research, the most interesting part is not the wearable itself however, it is the data it produces. In the current dissertation, we will focus on studying dedicated (online) data analysis platforms such as OFCs, which rely on data collection from mainly wearables of the health and fitness segment, but which, as stated above, increasingly show convergence with other wearables segments, in this case medical and healthcare wearables in particular.

3. (Online) data analysis platforms

Virtually every fitness tracker manufacturer accompagnies their devices with an online platform on which the data can be gathered and analyzed. For example Garmin has its 'Garmin Connect™' platform, Polar uses 'Polar Flow™', TomTom has its 'MySports™' platform and Fitbit makes use of their eponymous platform. We will term these '**brand-based platforms**', since they are designed to accompany and support technological devices, in this case fitness trackers, in their application.

Features of these brand-based platforms are mainly centred around self-monitoring and goal-setting features, based on the data collected with a fitness tracker of the respective brand. This primarily includes a diary-based interface on which the user can see on which days he/she was active, overall statistics on metrics such as average exercising time per week, average daily step counts and average resting heart reate. Then, per activity, for example a running activity, the user can see on a map where he/she ran see their average speed, distance covered, time spent running etc. Furthermore, when available on the platform, users can see specific analytics that provide them with insights on the progress they are making: i.e. is their fitness level improving? Lastly, some platforms make other features available to their users such as training plans and the possibility to set and work towards a certain fitness goal. Basically, these brand-based platforms are providing their users with detailed information or feedback on their (exercising) behavior and progress.

Research has demonstrated extensively that feedback through goal-setting and self-monitoring is an effective means to change behavior, at least in the shorter term (Broekhuizen, Kroeze, van Poppel, Oenema, & Brug, 2012; Hobbs et al., 2013; Ryan, Patrick, Deci, & Williams, 2008). Relapse into 'old habits' is alas quite common when feedback is no longer provided, seizes to deliver new insights or fails to address new needs. We then lose our motivation and fail to make our new behavior into new habits (Must et al., 1999; Shuger et al., 2011). Research on wearable use for example has shown that a third of people buying a fitness tracker stop using it within six months (Endeavour Partners, 2014). Moreover, it appears that, while 1 in 10 Americans owns a fitness tracker, more than half of them don't even use it (C. Arthur, 2014). Long-term engagement appears to be difficult to achieve. One of the reasons for this is that wearables and fitness apps are often too focused on delivering numbers and statistics in an isolated online environment, whilst it is well-known that having an exercise partner gives a higher chance of sustaining an exercise routine (Dishman, Sallis, & Orenstein, 1985; King & Frederiksen, 1984; Ransdell et al., 2003).

Similarly, while many intervention studies aimed at increasing physical activity using feedback or other self-regulatory approaches, including self-monitoring and goal-setting, provide good short-term results in terms of intervention adherence, long term effectiveness is often inconclusive or undetermined (Bravata, Smith-Spangler, Sundaram, & et al., 2007; Glynn et al., 2014; Gurman et al., 2012; Kahn et al., 2002; Van den Berg, Schoones, & Vlieland, 2007; van der Bij, Laurant, & Wensing, 2002). Many of these intervention studies mention the importance of social support in maintaining physical activity or an exercise regimen (Anderson, Winett, & Wojcik, 2007; Balatsoukas, Kennedy, Buchan, Powell, & Ainsworth, 2015; Beets, Cardinal, & Alderman, 2010).

4. …Enter Online Fitness Communities

There are platforms offered by independent service providers that offer the same self-monitoring, goal-setting, data analysis and visualisation affordances as those of the aformentioned brand-based platforms, except that they allow users to upload data collected with various apps or brands of fitness trackers. This implies that switching brands no longer means that one loses the data collected with the old tracker. Furthermore, in addition to the self-regulatory features found in technology/brand-based platforms, they also offer social networking features to their users. In contrast to the reports of wearable drop-out, they are experiencing growing user bases and succeed in keeping them engaged on the platform for longer terms (Barghava, 2016).

While being able to upload data from various wearable brands is very likely to be an important factor of their success, the main explanation of their success is likely to lie in their community-based approach, which leverages on connecting people and facilitating social interaction on the platform. The most prominent and succesful example of this community-based approach is Strava. Strava was founded to enable people to log and share their exercise behavior with the idea of being part of a team, even when there is no opportunity to 'physically' exercise together. The founders referred to it as 'a combination of a social network and a Quantified Self site ("Strava - From the Beginning," 2012). Since its launch in 2005, Strava's user base has been increasing rapidly, now containing over more than a million members worldwide ("A VC Lets a Bet Ride: the Story of Strava," 2013), generating over 2 million activities per week (Edwards, 2014; "A Global Data Set," 2014). This dissertation will use Strava as a prime example of the community-based approach of certain (online) data analysis platforms.

Other examples of similar community-based platforms offering features to induce social interaction between users are RunKeeper, which focuses largely on runners, Endomondo and Runtastic. We term these community-based platforms 'Online Fitness Communities' or OFCs, because on top of the activity feedback they deliver, a strong focus lies on offering social interaction features to their users. This in contrast to brand-based platforms, who mainly focus on analysis of the data that their wearables produce.

Providers of brand-based platforms did not miss the growing popularity of community-based platforms though, and in response, they increasingly start to offer social interaction features to their users. Garmin for example, included the possibility to connect with other users, and to like and comment their activities in the redesign of their Garmin Connect™ platform in 2014 (D. Arthur, 2014). Similarly, Polar Flow™, the data analysis platform for Polar-branded fitness trackers was updated with social features in 2015 (Ashcroft, 2015).

Little is known about the uptake of these social features in brand-based platforms however. The difference between brand-based platforms and community-based platforms is that in the first, the focus (still) lies on interpreting data from wearables. The social features have been added in response to the success of the latter, for which the focus has always been on connecting the users, especially in the case of Strava, with their personal data as a basis ("Strava - From the Beginning," 2012). Furthermore, network externalities play an important role in this regard (Wei & Lu, 2014). These network externalities refer to the influence that the perceived number of users of a product or service has on a person's use of that service/product (Katz & Shapiro, 1985). Especially when the product/service is embedded in a social context, the effect of network externalities can be substantial. This may imply that while brand-based platforms are catching up onto the community approach of community-based platforms, it may take some time for their users to follow, especially when they and their peers are already active on another community-based platform as well (Lin & Lu, 2011; Wei & Lu, 2014). Furthermore, research has demonstrated that the more peers one has on a social networking site, the more likely one is to have a continued intention to use it (Lin & Lu, 2011). This makes it less likely for users to switch between platforms. Lastly, brand-based platforms remain limited to uploading data collected with their brand of devices, which in terms of scalability, puts them behind community-based platforms which allow upload and synchronization of multiple brands of devices. The scalabilty of this 'brand indepedence' is crucial for the success of community-based platforms.

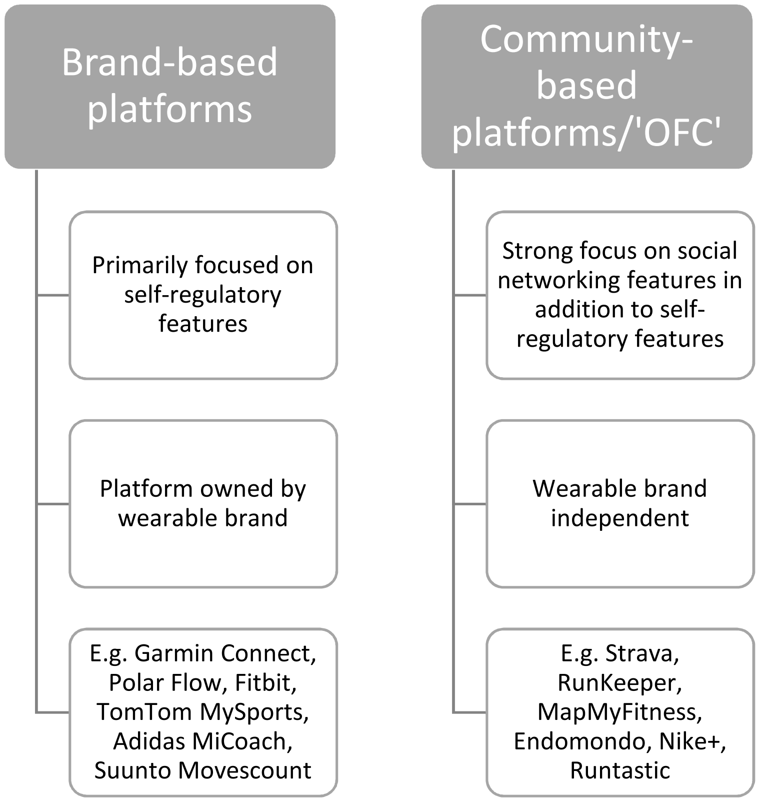

Figure 1 Brand-based vs. community-based platforms

Lastly, OFCs are sometimes referred to as ‘apps’. While this is not incorrect (most OFCs do have a mobile application that affords data collection, visualisation and social features), we consider the ‘app’ to be only a part of what makes up an OFC. The app is a medium through which the OFC and its affordances can be accessed. As such, when we refer to an OFC, for example Strava, we refer to *a community based online or mobile service or platform, offering data accumulation, data analysis and user interaction around one’s exercise behavior, for which data can be collected through various sources, including wearable activity trackers, fitness tracking smartphone applications or manual entry*. In this regard, a fitness app can be used for data collection, analysis and even social interaction affordances, but it is only a part of the service that is an OFC. In general, an OFC is a *gathering of people*, sharing and interacting online upon their exercise behavior.

CHAPTER TWO: ONLINE FITNESS COMMUNITIES UNPACKED

1. Introduction

People are increasingly connecting and interacting around their fitness and health data. These data are the basis of interaction in Online Fitness Communities or 'OFCs'. We argued that feedback on behavior, while appearing to be effective to change behavior in the short term, can lose its motivating power and become less engaging in the long(er) term. Embedding feedback within an (online) social environment may yield better results. OFCs apply a community-based approach in which users can be considered 'workout-buddies', but then in a virtual environment. In a way, OFCs want to give their users the experience of exercising with others, much like this would be the case when they would go running together for example. Activities that are often practiced individually, can thus be given a social component, albeit online. As such, OFCs as 'virtual communities' can serve as a substitute for or complement traditional communities such as a local running or cycling team, providing people with valuable resources that traditional communities offer such as companionship, a sense of belonging and social support. This chapter approaches OFCs from a virtual community perspective.

2. Communities

A signficant proportion of our social interactions takes place within communities (Mechant, 2012). For traditional communities, social interaction, communal relationships and physical co-location are considered to be the defining elements (Hillery, 1982). Indeed, communities are traditionally considered to be tightly knit, closed groups such as neighborhoods, workplaces or churches (Wellman, 1998, 2002). Bender's definition of a community (Bender, 1978, pp. 6-7) illustrates this school of thought: 'A community involves a limited number of people in a somewhat restricted social space or network held together by shared understandings and a sense of obligation. Relationships are close, often intimate, and usually face-to-face. Individuals are bound together by affective or emotional ties rather than by a perception of individual self-interest. There is a 'we-ness' in a community; one is a member'. Five distinct characteristics for these traditional communities can be extracted from this definition: a limited number of members, interaction within a social space or network, shared norms and values, close affective and emotional relationships and a 'sense of belonging' (Mechant, 2012).

This concept of communities in the traditional characterizations may be difficult to apply in a modern network society however. A paradigm shift has taken place starting in the 1960's from tightly knit communities, or 'little boxes' to a type of community that consists of more loose, diffused social connections between individuals, independent of geographical location (Wellman, 2002). One does no longer belong to one or two of these close communities specifically, but rather has membership in multiple groups or networks, without presence of strict hierachical and organizational structures, where autonomy precedes collectivity. Futhermore, mobile communication and internet have caused a shift from place-to-place to person-to-person communication, leading to the emergence of *Networked Individualism,* a form of social organization in which people are still connected to each other, but as individuals (Wellman, 2002). Rather than being part of one or two closely-knit communities, we are now part of various social networks, both online and offline, through which we connect to a substantially larger group of other individuals.

In this context, the concept of community required a new definition that better suits the characteristics of a network society. Wellman (2002) therefore defines a community as: "networks of interpersonal ties that provide sociability, support, information, a sense of belonging and social identity". The definition omits characteristics of traditional communities such as the limited number of members, face-to-face relationships (cf. Bender, 1978) and a physical co-location (Hillery, 1982). Indeed, the internet has created the opportunity to form vast and large scale communities, regardless of where the members are located in the world, using computer-mediated communication (CMC) rather than face-to-face interactions, which is the case in social networking sites as Facebook, LinkedIn or Twitter.

Community in new media contexts therefore emphasizes more on a 'feeling or sense of collectivity' than on geographical characteristics (Jankowski & Van Selm, 2000). Because these new communities are based on internet communication, they are also referred to as virtual communities.

3. Virtual communities

When communities predominantly exist in cyberspace they are often termed *virtual communities* (Rheingold, 1993; Van Dijk, 2006). In a virtual community, there is no need for members to live close to each other, to meet in person or share a physical co-location. It is rather the congregation and online interaction around common topics of interest or practices that define a virtual community as a community (Mechant, 2012). The question that rises is whether OFCs can in fact be considered as virtual communities?

The opportunity to engage in social interaction among community users is a key element in defining a virtual community as a community (Parks, 2011). Social Network Sites (SNS), such as Facebook, Twitter, MySpace and Instagram, are some of the most prominent examples of a virtual community. For a SNS to be considered as a virtual community, a user should in first instance be able to become a member, i.e. create a profile and visit this profile regularly. Second, a user should be able to engage in forms of self-expression, by for example customizing their profiles and providing a personal profile picture. Third, the user should be able to connect with other members using available tools such as 'friending', 'messaging' and 'commenting' (Parks, 2011). OFCs share many of these characteristics with SNSs. In contrast to a SNS as Facebook however, OFCs are much more focused on a shared interest and practice: exercising.

Furthermore, virtual communities are characterized by a clear purpose, based on a shared interest and practice, place, platform, population interaction structure and profit model (Porter, 2004).

The ***purpose*** of a virtual community forms the basis of interaction between community members. This purpose can be a certain practice or topic of interest (e.g. health, exercise behavior, art…). Exercise behavior is undoubtedly the shared interest and practice in OFCs. OFC users are all to some extent actively participating in some type of exercising, of which running, cycling and walking are most common. The *purpose* of OFCs then, is to bring these athletes together and offer them a platform on which they can monitor their behavior and connect to other athletes all over the world to share and interact on their activities.

Every (virtual) community is to some extent linked to a certain ***place***. Since virtual communities cannot be linked to a 'structural' place in the physical world, Porter (2004) suggests to apply Virnoche & Marx's (1997) 'degree of virtualness', which implies 'the extent to which community members share virtual space and/or physical space on an ongoing or intermittent basis' (Porter, 2004). The location of virtual communities can therefore exist on two levels: it can be hybrid, which implies that its members have interactions in both the physical and virtual world, thus making the virtual community an extension of an 'offline' community; and it can be exclusively virtual, which excludes physical and in-person relationships between the community members.

The type of ***platform*** on which a virtual community is built, is crucial for the degree of interaction between its members. A platform can offer either (near)-synchronous, asynchronous or hybrid interaction, where (near)-synchronous interaction implies that communication between members can exist in real-time, such as in chat rooms. Asynchronous interaction refers to a delay between messages, for example in email based communities of bulletin boards. Hybrid interaction platforms allow both previous types of interaction.

Porter (2004) distinguishes between three streams of research into ***interaction structures*** between members in virtual communities. A first stream considers virtual communities as *computer-supported social networks*, in which both strong and weak ties between members exist. While strong ties emerge from frequent supportive contact between members, weak ties also appear to demonstrate some supportive behavior between members. A second stream into virtual communities distinguishes between *small group structures* and *networked interaction structures* (Dholakia, Bagozzi, & Pearo, 2004). *Small groups* are marked by close ties and strong interaction between members. This implies that community members are well acquainted and share close personal relationships. Membership in these *small groups* is also often limited and exclusive. In *networked interaction structures*, community members are more loosely connected and socially & geographically dispersed. These networks generally have a more utilitarian function, for example for information gathering (Porter, 2004). The third research stream *opposes virtual communities to so-called 'virtual publics'*, which are open (i.e. not password protected) platforms. Membership is often only temporal and commitment to interaction in the community is low and therefore often only limited interaction can be noticed (Komito, 1998).

The last characteristic is the ***profit model*** behind a community. Briefly stated, virtual communities can be either revenue-generating or non-revenue generating. They can do so by being a 'community enabler', a sharing/trading community or a website feature of a company (Krishnamurthy, 2002). The first is the broadest category with communities focused on a wide variety of topics or practices, generating revenue through advertising or subscription fees. Sharing/trading communities allow their users to trade goods or services, such as eBay. Company featured communities are a company's way to bond with its customers and as such generate profit (Porter, 2004). OFCs are commonly revenue-generating communities through advertising, subscription fees and extra services.

To be considered as a virtual community in this thesis, (online) data analysis platforms should meet the five criteria listed above to certain extent. This implies that on top of a clear purpose and business model, interaction between members in terms of place (online, offline of both), structure (networked interaction, virtual public or small groups) and platform characteristics ((near)-synchronous, asynchronous or both), should be facilitated. While purpose and profit model of OFCs do not require empirical research to be derived; for place, platform, population interaction structure this is the case. In the empirical research part of this thesis, Chapter four will be devoted to assessing these interaction characteristics of OFCs based on various data sources.

4. The Quantified Self movement: an illustration of online communities focusing on personal informatics

The notion of a community that interacts on the basis of individual members' technologically logged activities, is not new. People have, for example, always been monitoring their weight, and athletes have long logged their activities using pen and paper (or later via Excel sheets). The difference between those earlier forms of collecting health-related data and now is that wearable technology has facilitated the practice by allowing us to (1) capture the data on a much larger scale, (2) with a higher frequency and (3) on parameters we were not able to collect before, at least not without very expensive lab tests or equipment (Kas, 2014), such as blood glucose levels and continuous heart rate monitoring. Wearables have thus lowered the threshold substantially for people to log their own health and activity patterns.

Over the past decade, society has witnessed the rise of a very lively and growing subculture of 'life-loggers' who keep track of as many aspects of their life as possible, using a wide array of technological developments. This movement is referred to as the 'Quantified Self' (Swan, 2012b, 2013). Although life-loggers, or 'Quantified Selvers', oftentimes track more than their health and activity patterns, the latter are usually an important part of their logging activities.

The idea behind the Quantified Self (or 'QS') is to measure every possible aspect of life in order to learn about oneself and to improve one's quality of life. The movement was allegedly founded by Wired Journalists Gary Wolf and Kevin Kelly in 2007 after witnessing a trend towards gathering and sharing data on personal genomics and biometrics (Wolf, 2011). The movement started organizing meet-ups for these early stage 'life loggers' and has since become a global community, focused on measuring patterns in self-collected data on a broad range of parameters. Fitness parameters are evidently among those most frequently collected, given the widespread availability of fitness trackers that afford measuring heart rate (increasingly through optical HR, which avoids having to use cumbersome HR chest straps, although measurement accuracy is often questioned), energy expenditure, weight, steps taken, location tracking through GPS, sleep tracking and much more. Increasingly, other sensors are becoming available on a consumer grade, such as environmental sensors measuring indoor and outdoor air quality, humidity and pollution. Furthermore, life-loggers often fall back to manual data collection using Excel spreadsheets or basic applications that allow them to capture information that no sensors can collect to date, such as cups of coffee per day, amounts of water, fruit servings and much more. Moreover, open data, such as meteorological data, air quality data and spatial planning data is increasingly allowing to add context related parameters to their data which affords putting the interpretation in an (environmental) context.

The purpose of the Quantified Self movement is twofold (Swan, 2013): First, the purpose lies in combining various parameters and data types, often through basic correlations, in order to identify patterns in one's life, for example the influence of the number of cups of coffee one drinks during the day on work productivity. Ultimately, the outcome of this is a better understanding of how various factors affect our lives in order to make informed choices to improve our quality of life. The second purpose of the movement is to collectively think about how certain parameters that cannot be captured today could be measured. In order to achieve this, the Quantified Self movement aims to connect life-loggers both online (on dedicated forums such as forum.quantifiedself.com) and offline in meet-ups and conferences in which three questions form the thread through all discussions: 'what did you measure', 'how did you measure it' and 'what did you learn' (Swan, 2013).

OFCs can be situated within this larger QS movement as platforms in which users can log and interact upon their exercise behavior on a regular basis with the purpose of learning about their behavior and working towards specific health related goals.

5. Conclusion

This chapter's objective was to lay out what the characteristics of (online) communities are and how this can be applied to OFCs as a relatively new phenomenon within social media. Generally, OFCs can be considered to have much of the characteristics and requirements for an online platform to be considered as an enabler of a virtual community. OFCs enable their users to connect and interact on their common interest in and practice of exercising whilst not requiring any physical co-location.

Activities as cycling and especially running are increasingly practiced individually (Borgers et al., 2016; Scheerder & Vos, 2011). This has its advantages as people are not bounded to fixed training hours and as such can practice their activities at any moment that seems fit. Having one or more 'workout buddies' and not having to exercise alone is in fact one of the key reasons why people join sports teams or clubs. When exercising alone however, one cannot enjoy the social aspects of being part of a team. By means of their social interaction features, OFCs may have the potential to partly remedy this by enabling people to connect and stay in touch with others and 'virtually' train together, when 'offline' exercising together is not possible (Tervoort, 2016). Nonetheless, a connection between the OFC as a virtual community with actual running teams is possible, which illustrates the hybridity of an OFC's 'place' characteristics. Essentially, OFCs then can be considered to be either an extension or replacement (or both), of local exercise communities. To some extent, they may have the ability to offer 'isolated' athletes a feeling of community, recognition, support and belonging, which are essential when attempting to motivate people to become and stay more physically active. In chapter five of this thesis, we specifically address the provision and reception of online social support for exercise behavior through OFC use by means of two studies.

CHAPTER THREE: TOWARDS A BLUEPRINT FOR INCLUDING SOCIAL AFFORDANCES TO FOSTER PLATFORM ENGAGEMENT

1. Introduction

Data about our physical activity, whether collected manually or through wearable technology, delivers valuable feedback from which informed decisions can be made about health behavior. Nevertheless, while this feedback can be helpful in first instance, for some people it can be either too complex or not informative, or they may lose interest once the novelty factor and informativeness of their fitness tracker wears off (Lazar et al., 2015). Therefore, while fitness trackers can deliver useful data and feedback that works as a motivator in the short term, these data alone may not be engaging enough and lack the power to motivate people to sustain their active behavior in the long term. High cessation of fitness tracker use in the first six months after adoption is a clear indication of this (Clawson et al., 2015; Lazar et al., 2015; Endeavour Partners, 2014). This, however, does not necessarily imply that cessation of fitness tracker use automatically implies cessation of physical activity. A user could definitely sustain this behavior without the use of the fitness tracker. Maybe he/she learned enough from the data, adapted his/her behavior, and requires no further use of the fitness tracker (or its data analysis platform). However, if the feedback from the data was the reason why a fitness tracker was purchased and it (or its data analyis platform) fails to create engagement, some may already drop-out after a limited number of logins and as such, the likelihood that he/she will further engage in physical activity is likely to decrease.

Increasing both behavioral and platform engagement to foster sustainment of healthy behaviors may require more than delivering feedback. It is well-known that having people to exercise with, results in better exercise adherence and increased motivation (Ransdell et al., 2003; Wing & Jeffery, 1999), and so does receiving social support for exercising from significant others (Anderson et al., 2007; Rovniak, Anderson, Winett, & Stephens, 2002). Online platforms that enable users to interact and support each other, in addition to data visualisation and feedback, may therefore be more prefereable than those that only focus on self-regulatory feedback. OFCs attempt to connect people based on their exercise behavior. This community approach is expected to be better at motivating people to stay physically active than only providing feedback on their behavior based on the data they collect with fitness trackers. In order to grasp this crucial motivational aspect, we rely on Self-Determination Theory.

2. Self-determination and intrinsically motivated behavior

Motivation is inevitably linked to the established Self-Determination Theory of motivation (SDT) (Deci & Ryan, 2008; Deci & Ryan, 2010). According to SDT, humans inherently strive for personal development and growth (Deci & Vansteenkiste, 2004). The driving forces behind their aspirations can be either internal (intrinsic motivation) or external (extrinsic motivation). Intrinsic motivation implies that one engages in behavior regardless of any external rewards and entirely for the enjoyment of it (Deci & Ryan, 1975). In short, when one is intrinsically motivated, one engages in it or the activity itself, not for any reward attached to it. The basis of this intrinsically motivated behavior is the aspiration for fulfilment of three basic psychological needs: autonomy, competence and relatedness.

Autonomy refers to the need to be in control of one's life, to the perceived source of control of one's behavior (Deci & Ryan, 2002). When a person perceives that his behavior is controlled through an external factor (i.e. external locus/source of control), he tends to be less motivated to engage in the behavior at hand. Vice versa, one tends to be more motivated the more one has a clear rationale for engaging in certain behavior. In other words: when the behavior is self-determined. Competence is a person's need to feel effective or successful in his/her undertakings (Deci & Ryan, 2008, 2010). Having actions resulting in desired outcomes is critical in a motivational context, as it enhances one's sense of competence (Beachboard, Beachboard, Li, & Adkison, 2011). Lastly, relatedness (or belongingness, connectedness) comprises a person's need to have meaningful relationships with significant others and one's community. In contrast to autonomy and competence, relatedness is not specifically targeted at reaching a goal or outcome, but rather concerned with 'being with others in secure communion or unity' (Deci & Ryan, 2002, p. 7). Fulfilment of these needs ultimately leads to personal growth and life satisfaction.

On the other hand, when behavior is engaged in for the attainment of an external outcome or reward, we consider it to be extrinsically motivated (Ryan & Deci, 2000a). Examples of such behaviors are doing homework to get good grades or doing the dishes to get an allowance: these behaviors are usually not engaged in because one likes to do them, but for an external outcome. Extrinsically motivated behaviors differ, however, in the degree to which they are autonomous. Ryan & Deci (2000a) use the example of doing homework to avoid a reprimand of their parents or doing homework in pursuit of a great professional career as two extrinsically motivated behaviors, yet with a different level of autonomy. This refers to the different levels of internalization and integration of extrinsically motivated behavior, of which *integrated regulation* is the most autonomous form of extrinsically motivated behavior. While this type of behavior is largely self-determined, it can't be considered to be intrinsically motivated because it is still instrumental in nature. More autonomous extrinsic behaviors are however associated with fewer drop-out and increased engagement (Ryan & Deci, 2000a). Thus, focusing on fostering internalization can result in improved engagement in behavior. Therefore, focus should be placed on improving one's sense of autonomy and competence on the one hand and one's sense of relatedness on the other. Behavior that is valued by significant others will be more easily copied, creating a sense of belonging to a group. Furthermore, improving one's self-efficacy will nurture one's sense of competence. Providing people with a clear rationale as to why they should be engaging in certain behavior, i.e. supporting their sense of autonomy, remains critical however, as only this will lead to internalization of the behavior. In a health-care context, maximizing the experience of these basic needs, increases the likelihood of internalization of health-related behavior and better adherence (Ryan et al., 2008).

In sum, in order to motivate people to become and stay active with assistance of technology, all three basic needs should be addressed to increase the chance of sustaining active behavior. Data analysis platforms limited to visualizing the data collected with fitness trackers and offering self-monitoring features through for example goal-setting and progress reports, which is the case for many of the currently existing platforms, can be successful at fostering people's sense of competence and autonomy, but lack the ability to tap into their need for belonging and relatedness. They are an environment in which the user is isolated from others with his data. In order to create a stronger motivation, these platforms should be supplemented with social features, enabling the user to reach out and interact with others on the platform or on other social media, an approach used by OFCs such as Strava. The utilities of an (information) technology, enabled through its features is often termed an 'affordance'. These affordances are an essential concept in this dissertation. We will identify the motivational affordances of OFCs for (recreational) athletes and assess to what extent they can address their motivational needs in terms of autonomy, competence and relatedness.

3. OFC Affordances

While originally developed to describe the actionable relationship between the world and its actors (persons or animals) (Gibson, 2014), the concept of affordances is increasingly studied in social sciences, especially in relation to the use of digital media. 'Affordance' refers to the perceived utility of a technology and its technological properties (Norman, 1999; Schrock, 2015). In other words, the technological capabilities or specifications of a technology or a digital medium provide its users with functionalities or features that offer them opportunities to interact with and take advantage of the technology in a meaningful way. Affordances are then realized in the interactions between the individual user and the object in a specific context and environment (Mechant, 2012). A mobile phone, for example, offers its users portability, availability, locatability, and multimediality through its technological components (Schrock, 2015). Various typologies of affordances have been defined: for example interpersonal and conversational affordances (Fraser & Reid, 2010), informational, relational, temporal and spatial social affordances (Hogan, 2009) and motivational affordances (Zhang, 2008).

The concept of **motivational affordances** is closely linked to SDT. More specifically, motivational affordances occur when a person experiences basic needs satisfaction through use of object features (Deterding, 2011). ICT design directed towards motivating behavior or behavior change should therefore support this attainment of basic needs (Zhang, 2008).

OFC features & affordances

The basic practice that lies at the heart of an OFC is quantification of exercise behavior. The data that result from this practice can be applied as input for OFCs and more specifically, for the various features that are present in OFCs that enable users to work with their data. Two categories of OFC features can be distinguished: (1) features that visualize or interpret the collected data and enable the user to for example set goals and monitor progress (self-regulatory features) and (2) features that allow the users to connect and interact with other community members upon their data and activities (social features). Though interaction with these two feature categories, using their personal data as input, OFC users can realize certain motivational affordances (Zhang, 2008): self-regulatory affordances and social affordances. Through the use of OFC features and the resulting affordances, OFC users can experience basic needs satisfaction. Figure 2 demonstrates the relationship between quantification, OFC features and motivational affordances.

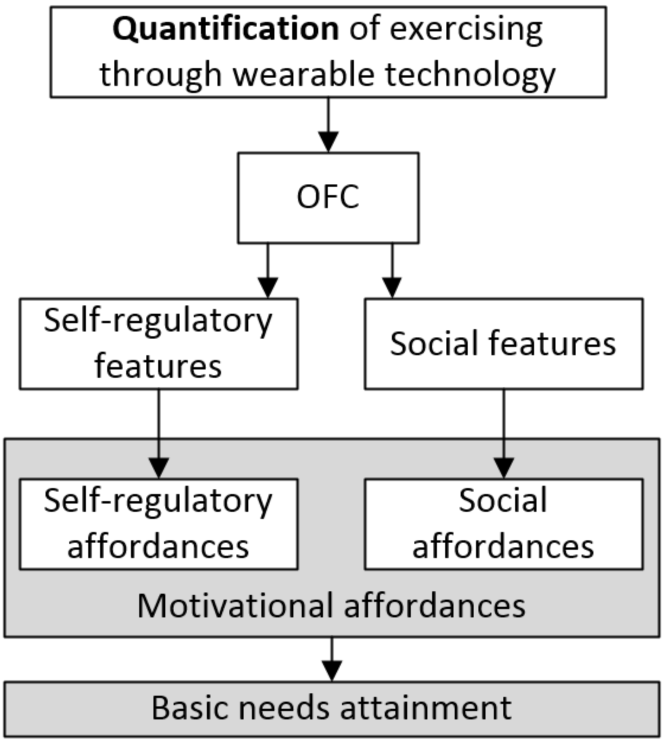

Figure 2 Relationship between quantification, OFC features and motivational affordances

3.1 Self-regulatory affordances

3.1.1 Self-regulation

Increasing physical activity through self-regulation techniques is a strategy that is often followed in intervention studies, mostly through self-monitoring of behavior and goal-setting, based on self-monitoring, with promising results (Anderson-Bill, Winett, & Wojcik, 2011; Anderson et al., 2007; Joseph et al., 2013; Koring et al., 2012; McKay, King, Eakin, Seeley, & Glasgow, 2001; Michie, Abraham, Whittington, McAteer, & Gupta, 2009) (Shilts, Horowitz, & Townsend, 2004), especially when goals are self-set, achievable and sufficient feedback is provided (Munson & Consolvo, 2012).

Being able to self-regulate one's own behavior implies the ability to exercise control over the behavior at hand, which according to SDT, would result in a greater feeling or sense of autonomy and competence (Bandura, 1991; Ryan & Deci, 2000b). Self-regulation lies at the basis of human goal-oriented behavior. It is a phased process that requires individuals to exercise influence over their motivations and behavior through self-reflection and self-reaction. Self-regulation basically has three underlying functions, self-monitoring, goal-setting and self-evaluation (Bandura, 1991).

Self-monitoring implies that people observe and reflect upon their actions and behavior. The major outcome of self-monitoring is information on our knowledge about one's behavior, which allows one to guide and plan future behavior. This planning or goal-setting is a second subsystem of self-regulation. Observing their behavior incites people to pursue personal improvement and thus implies a self-motivating function of self-monitoring. According to goal-setting theory, 4 steps to successful behavior change through goal-setting can be distinguished: recognizing a need for change, setting an achievable goal, monitoring progress and rewarding oneself for achieving the goal (Cullen, Baranowski, & Smith, 2001; Locke & Latham, 1994). Goal-setting leads to better performance by creating higher expectations on behavior and leading to satisfaction upon completion of a goal. Finally, the self-evaluative function of self-regulation comes into play. Self-evaluation plays a crucial role in motivation. By getting information and feedback on behavior, people are impulsively urged to set goals and work towards self-improvement (Bandura & Cervone, 1983).

Furthermore, personal factors play an important role. If people do not *value a behavior* that requires change and as such have low expectations towards the outcomes of changed behavior, they will be less motivated to take action. SDT connects this valuation on behavior to the level of its internalization. Extrinsically motivated behaviors will only be internalized, i.e. self-determined, when one has a clear rationale for it (Ryan & Deci, 2000b). In the context of exercise behavior, the rationale is commonly the desire to live a healthier life. *Self-efficacy* then, is a concept crucial to self-regulation. It represents the believe in one's abilities to effectively perform or exercise control over a behavior (Bandura, 2004), and is highly decisive in self-monitoring, goal-setting and self-reaction. The more capable one considers oneself to be, the more likely one is to assign failures to lack of effort and set higher goals for example. Self-efficacy is closely related to the basic need of competence (Bandura & Schunk, 1981; Coleman & Karraker, 2003). People with a high sense of self-efficacy, generally consider themselves more competent in the behavior at hand.

In order to facilitate successful self-regulatory behavior, the sooner information on the behavior is provided after performing the actual behavior, the more effective it is in fostering change (*temporal proximity of self-monitoring)* (Bandura, 1991). Furthermore, the information needs to be understandable in order to be effective (*informativeness of performance feedback)* (Bandura, 1991). If one cannot deduce the necessary information for behavior change from the feedback that is provided, behavior change will not be as effective. It is therefore crucial that fitness trackers and their accompanying data analysis platforms deliver feedback close to the behavior and in a comprehensive way. This mostly tends to be the case, with fitness trackers increasingly being equipped with a display that provides feedback during the behavior or some fitness apps giving auditory feedback while exercising. Post-workout upload options facilitate consultation of the activity on data analysis platforms virtually immediately after uploading.

3.1.2 Self-monitoring & goal-setting features in OFCs

In OFCs, self-regulation makes up a large part of the available features. In essence, these features mainly enable self-monitoring and goal-setting affordances (Zhang, 2008) and consequently enable users to monitor their exercise behavior, set goals accordingly and monitor their progress. Examples of these features are a calendar function which quickly visualizes how often/how long the user has exercised in the last week/month/year and specify a goal towards which the user wants to progress, for example progressing towards running 5K within 8 weeks.

Features such as goal-setting, self-monitoring, progress reports can support a user's sense of competence and autonomy by giving them data-based feedback and rewards for goal-attainment (Gagné & Deci, 2005). Increasingly, OFCs are assigning virtual rewards to support goal-setting. The use of these virtual rewards is increasingly termed 'gamification' (Deterding, Dixon, Khaled, & Nacke, 2011).

3.1.3 Gamification features for self-regulation: the role of virtual rewards

Gamification is the use of elements and mechanics commonly found in digital games in non-game contexts in attempt to increase motivation, user retention, engagement and enjoyment (Deterding et al., 2011; Simões, Redondo, & Vilas, 2013). This strategy is increasingly followed to increase the enjoyment of less enjoyable tasks or activities and as such influence the desired outcomes, i.e. behavior change. Although gamification is mostly applied in the context of digital technology, the concept is equally applicable to non-digital contexts (Groh, 2012).

The goal of implementing game elements in non-game contexts is that by using extrinsic rewards such as virtual rewards like badges and achievements can improve a person's sense of autonomy, relatedness and competence (Shi, Cristea, Hadzidedic, & Dervishalidovic, 2014). Widespread use of the term 'gamification' began around 2010 (Deterding et al., 2011). Its applicability for motivating behavior change made it popular in fields including digital marketing, health, workplace and education. In the mobile application ecosystem, gamification quickly became established as a means of fostering user retention, especially within the health app industry and its application has become widespread in health and fitness apps available in the app stores (Lister et al., 2014). Six gamification elements in health apps are commonly used: leaderboards, levels, digital rewards, real-world prizes, competitions, and social or peer pressure (Lister, West, Cannon, Sax, & Brodegard, 2014). Most applications contain only one to three of these gamification elements, however. Social or peer pressure appears to be most commonly used, followed by virtual/digital rewards, competition and leaderboards.

The behavioral strategies underlying gamification that target motivation are incentivization (giving rewards), providing social support, goal-setting, improving self-efficacy and cognitive strategies (improving knowledge on the behavior at hand) (Lister et al., 2014). Some gamification elements can be used in support of self-regulatory affordances of OFCs. This is especially the case for virtual rewards. They are the most basic and commonly used form of gamification. They can mostly be earned as *badges* or *achievements* (Hamari, 2015), e .g. receiving a gold medal for taking 10,000 steps in one day. The use of badges as a reward system is closely related to the concept of goal-setting in the context of self-regulation. Badges form a direct feedback on the behavior at hand, as a completion of a clearly defined goal. This feedback is known to foster further desire for self-improvement and as such, badges would be helpful for increasing a person's sense of competence (Boticki, Baksa, Seow, & Looi, 2015).

In sum, self-regulatory affordances, enabled through self-monitoring, goal-setting and certain gamification features are directed towards helping people to experience an improved sense of autonomy and competence by providing them with information on their behavior and letting them experience success in their endeavors. We argue that platforms which enable only these self-regulatory affordances to some extent fail to address a person's need for relatedness by focusing too much on his/her data in an isolated environment. Social features should accommodate this gap to a certain extent.

3.2 Social affordances

3.2.1 Social interaction & social support

Social features in OFCs are directed at allowing people to interact upon and reinforce and support each other in their exercise behavior. We are all, to some extent, part of social networks and communities. Our interactions in these networks with others influence our role in our daily lives on various levels.

According to SDT, our need to have meaningful relationships with significant others, lies at the core of our intrinsic motivation (Ryan & Deci, 2000b). Through these relationships, we experience both positive and negative feedback on our behavior. Positive feedback has been demonstrated to have positive influence on our motivation and enjoyment and as such it fuels our sense of competence and autonomy (Murcia, Román, Galindo, Alonso, & González-Cutre, 2008). Furthermore, according to Cognitive Evaluation Theory, a sub theory of SDT, social feedback, in the form of recognition and positive reinforcement by others will strengthen one's sense of competence and as such enhance intrinsic motivation, under the condition that the individual performing the behavior has a clear rationale for it and thus considers the behavior to be self-determined (Deci & Ryan, 1975). This social support will also strengthen the sense of relatedness to caring others (Ryan & Deci, 2000a). Social support from our peers is crucial in this regard.

Social support is a product of our social interactions and relationships with others. It is an important coping mechanism for stressful situations. It has been defined in various ways with social ties, through which social support is generally delivered, as recurring concept (e.g. Hirsch, 1985; N. Lin, Simeone, Ensel, & Kuo, 1979). It is the 'perception and actuality that one is cared for, has assistance available from other people (spouse, relatives and friends) and that one is part of a supportive social network' (Cooke, Rossmann, McCubbin, & Patterson, 1988; Odongo, Makumbi, Kalungi, & Galukande, 2015). Social support is an important concept in the context of physical activity. In fact, it has been found to have similar outcomes as physical activity, being both physiological improvements in immunity and cardiovascular health (Uchino, Cacioppo, & Kiecolt-

Glaser, 1996) and psychological coping with for example stress (S. Cobb, 1976; Halbesleben, 2006; Heinrichs, Baumgartner, Kirschbaum, & Ehlert, 2003).

Sources of social support are relatively widespread. In the context of exercise behavior, friends, family and significant others are traditionally considered to be the most predominant sources, depending on the population at hand (Anderssen & Wold, 1992; Prochaska, Rodgers, & Sallis, 2002). In the last decades, the emergence of computer mediated communication (CMC) and online social networks have opened the opportunity for seeking and receiving social support in an online environment. Online health communities are an excellent example of how people with specific illnesses seek and receive social support. Indeed, CMC has several advantages over face-to-face communication. A large audience can be reached 24/7 making support readily available (Walther & Boyd, 2002). This audience stretches beyond those known in person or what Courtois et al. (2011) term 'identified offline public'. In an online environment, interactions can be established with 'identified and unidentified online publics' (Courtois et al., 2011). Both of these refer to those with whom one doesn't have a physical connection. The identified online public consists of those with whom one is familiar, whereas the unidentified online public entails those with whom one has no connection. The addition of the online publics has thus broadened the scope of social support delivery channels. Furthermore, the anonymity of CMC makes it easier to seek support for sensitive issues that are less easily addressed in face-to-face encounters (Lange, Van De Ven, & Schrieken, 2003; Lewandowski, Rosenberg, Jordan Parks, & Siegel, 2011). OFCs distinguish themselves from other (online) data analysis platforms through the focus on and availability of features that enable their users to create a social environment online or a virtual community in which they can interact with and support each other for their exercise behavior. Two categories of these social features can be distinguished: features directed at interaction and communication between users and social gamification elements.

3.2.2 Social affordances through social interaction features in OFCs

Social affordances are conceived as the interplay between technology, interaction and social context in which the interaction takes place. As such, information and communication technology provides its users with the technological capabilities to facilitate online social interaction (Hsieh, 2012). E-mail, for example, affords asynchronous communication while instant messaging affords (near)-synchronous communication. Social Network Sites (SNS), a prominent example of a virtual community, are perhaps the obvious example of how technology facilitates social affordances. SNSs, as web-based communication platforms, enable their users to form and maintain large networks of social connections online through various technological features (Ellison, Steinfield, & Lampe, 2011).

Social interaction features in OFCs are implemented to stimulate connection and conversations between members and as such, they create social affordances for OFC users. Parks (2011) distinguishes between social affordances of *membership*, *personal expression* and *connection* on social network sites. Social affordances related to membership specifically refer to the option to create a private or a public profile page. With private profiles, which require users to 'request' friendship, a virtual community is more likely to contain 'strong ties' between its members, i.e. members will be more likely to be personally acquainted. OFCs generally have the option of setting a profile to public or private. In Strava for example, profiles are initially set to public, though one has to be a Strava member to access the profile. Social affordances for personal expression refer to features allowing a user to personalize his/her profile with for example a personal profile picture and to post personal content on the profile page. Reid & Reid (2010) refer to these as 'expressive' or 'interpersonal' social affordances. In OFCs, displaying long distances, high average speed or power outputs during bike rides for example to other users can be seen as a way of self-expression as an athlete. Third, social affordances of connection are perhaps the most important in creating cohesion and a sense of belonging to a virtual community (Parks, 2011). Connecting, 'following' or 'friending', i.e. asking another member to establish a connection in the community are basic features. Users can follow other athletes (both identified and unidentified) and be followed back by them. Once a connection has been established, users can interact with each other to a certain degree, depending on the platform type. Reid & Reid (2010) refer to these as 'conversational' social affordances.

As a result of these social affordances, positive social feedback and support can be exchanged between users, in supporting their exercise behavior. Liking and commenting someone's activities can be easy ways of providing social support, *recognition* or endorsing messages to each other. On Strava for example, they can give 'Kudos', which is the Strava equivalent of a Facebook 'like', to activities posted by another Strava user as a means of endorsing each other for achievements, and/or comment on their activity. Social interaction on OFC's is also an important contributor to their popularity. Sharing physical activities online with other users, endorsing and getting endorsed for achievements by online peers has added a new 'online' dimension or experience to exercise behavior, which, when met with positive feedback can enhance one's sense of competence and belonging (Murcia et al., 2008).

Furthermore, most OFCs allow users to share their achievements on other social media like Facebook or Twitter, which allows them to increase their reach and opens another channel for social feedback and support.

3.2.3 Social gamification features in OFCs

Lastly, social gamification features, mostly present in the form of social competition, are used to let the user experience a sense of competence in relation to others on the platform. Commonly used types of social gamification features are leaderboards and social comparison features. Leaderboards visualize whom in the user's network is performing best at the activity that is being gamified. Examples of this are leaderboards on for example who took the most steps during the past week or who ran the fastest time on a certain route.

This social comparison, occurring when people compare their achievements and badges with each other, is assumed to have a positive influence on behavior. Social proof theory (Cialdini, 2009; Hamari, 2015) states that people are more likely to engage in behavior when they see others performing that same behavior (Hamari, 2015). Social comparison then, allows users to compare their achievements to those of other users of the OFC. Moreover, social comparison also affords others to give recognition, i.e. social support, to the behavior at hand. On the other hand, social comparison could become discouraging and result in a negative perception of one's self-efficacy and competence when one is constantly outperformed by significant others (Bandura, 1991). It is therefore important that goals are set realistically and comparison is made to comparable others. Furthermore, self-comparison, as opposed to social comparison, could constitute an alternative strategy in order to limit deleterious effects of constant unfavorable comparisons. Personal challenges in OFCs for example, imply that a user is challenged to for example raise his/her step count from 8000 to 10000 steps per day.

Virtual rewards, which were already discussed under self-regulation affordances of OFCs, also entail a social side when visible to other users. They deliver proof of one's engagement and progress in certain behavior and when met with recognition and appraisal from other users, can likewise be considered a social gamification feature. As such, virtual rewards can let OFC users experience satisfaction of their need for both competence and relatedness.

4. Conclusion

Lack of physical activity has incontestable negative health consequences. Although convincing people of the benefits of regular physical activity is not that hard, encouraging them to start moving and subsequently, help them to keep up their healthier behavior is harder to achieve. A number of technological developments are increasingly attempting to assist people in being more active. Wearable technology is at the base of this development. Fitness trackers have afforded automated and large scale physical activity data and their uptake is increasing. Most of these commercially available devices have a built-in display and/or come with an online or mobile platform that visualizes these data, for example step counts, energy expenditure and heart rate. Nevertheless, many of these devices are as quickly abandoned as they were adopted and in many cases, no behavior change is achieved. While the data they collect are undeniably valuable and useful as feedback on people's behavior, they often appear to fail to engage people to stay active in the longer term.

However, a number of online and/or mobile platforms are gaining popularity and succeed in sustaining an active user base. These platforms have taken a community-based approach with an integration of social interaction features and self-regulatory features to afford their users a motivating experience, based on the data collected with their fitness trackers. It is our hypothesis that offering features that help a user realize a combination of self-regulatory and social affordances, both motivational affordances, presents a promising mix of elements that succeeds in addressing the basic need for autonomy, competence and relatedness, which is necessary to effectively maintain motivation for behavioral change.

We called these platforms Online Fitness Communities, as the social interaction element creates an engaging atmosphere based on a social experience with (online) peers. The interaction in such a community allows the members to motivate each other, provide social support, encouragements and companionship based on the activities logged with wearable devices. In sum, OFCs provide their users with self-regulatory features for analyzing and interpreting their personal data, but they combine this in a seemingly successful way with engagement through social interaction features. The social affordances, realized through the use of these social features are expected to deliver a substantial added value over offering only self-regulatory affordances. Consequently, a number of questions arise.

RQ1. What is the role of the social interaction that is afforded on OFCs?

Social support is undoubtedly an import element in health behavior (change). The social interaction features in OFCs afford their users to interact and as such endorse and support each other for their exercising. A first question that rises here is: do OFC users support each other through the social features they have at their disposal? Do they post encouraging and supportive messages to another users activities? Do they 'Like' each other's activities?

Second, OFCs also afford their users to share their activities outside of the platform, with their online peers on social networking sites as Facebook and Twitter. The question that poses itself here is why people engage in this behavior? Why do they want to share their exercise behavior on social networking sites? Do they actively seek social support and recognition by sharing their activities?

Chapter 5 presents two studies to answer these questions.

RQ2. How are motivations for exercising linked to the affordances of OFCs?

All people to some extent seek fulfillment of their basic need for competence, autonomy and relatedness. In this regard, people have diverging motivations for exercising. Completing a marathon, adopting healthier lifestyle, losing weight or social contact with others are all examples of goals people want to attain through exercise behavior and attainment of these goals ultimately leads to basic needs fulfilment to a certain extent. OFCs can accommodate and support motivation for these behaviors through their self-regulatory and social interaction affordances. The question that poses itself is whether OFC features are indeed used as such? In other words, do people who have social motivations for exercising, for example meeting new people, use the social OFC features more? Or do people who want to attain a specific goal exclusively use the self-regulatory features? Or do they use the social features as well, in order to for example seek support from their environment in their attempt to attain their goal? In chapter six, we will link 4 common (physical, social, achievement and psychological) (Masters, Ogles, & Jolton, 1993) motivations for running to the self-regulatory and social affordances of OFCs to answer this research question.

RQ3. Does social interaction contribute to a sustained use of the platform?

One of the basic assumptions of this dissertation is that offering social interaction features in combination with self-regulatory features can result in a more engaging and motivating platform experience. People start using fitness trackers for the feedback on their behavior these tools deliver in their attempt to adopt healthier lifestyles. It is very common, however, that people stop using them once the novelty and informativeness wears off. The platforms that unlock the data of these fitness trackers are largely limited to self-regulatory features. It appears that 'something' is needed to keep their data informative and engaging. We therefore assume, based on the apparent success of existing OFCs, that offering social features can be successful in keeping users active on the platform and as such, indirectly lead to sustained exercise behavior. It is our assumption that while people are initially mainly interested in getting data-based feedback on their behavior, social affordances are vital to keep them motivated. That question that must be answered is therefore: does social interaction contribute to sustained platform use? Chapter seven presents a study conducted to answer this question.

5. …Towards a blueprint for including social affordances to foster platform engagement?

If social interaction features afford added value to self-regulatory features, they could have a wide range of applications to make data analysis platform more effective at supporting behavior change. The answers to the research questions can provide valuable insights for future (online) data analysis platform development, fitness tracker interfaces and physical activity intervention studies.

Therefore, the objective of this doctoral thesis is ***to develop a research-based framework that unravels the underlying reasons for continued OFC use.*** Consequently, the outcome of this dissertation, based on the insights gained in the study of OFCs, should be the development of a blueprint, applicable to guide the development of engaging dashboards, platforms, communities… designed to support sustainable behavior (change) in various populations. Quantification of behavior, which can be done manually but preferably technology-assisted, is the base layer of this blueprint. The data can then be used to feed self-regulatory and social interaction features. The ultimate goal is to strengthen and sustain people's motivation for various behaviors, through the use of technology and by means of an engaging platform. In this dissertation, the framework will be developed with a focus on exercise behavior, logged in OFCs. Figure 3 presents the theoretical framework of this thesis and the accompanying research questions and their respective studies, presented in the following part of this thesis.

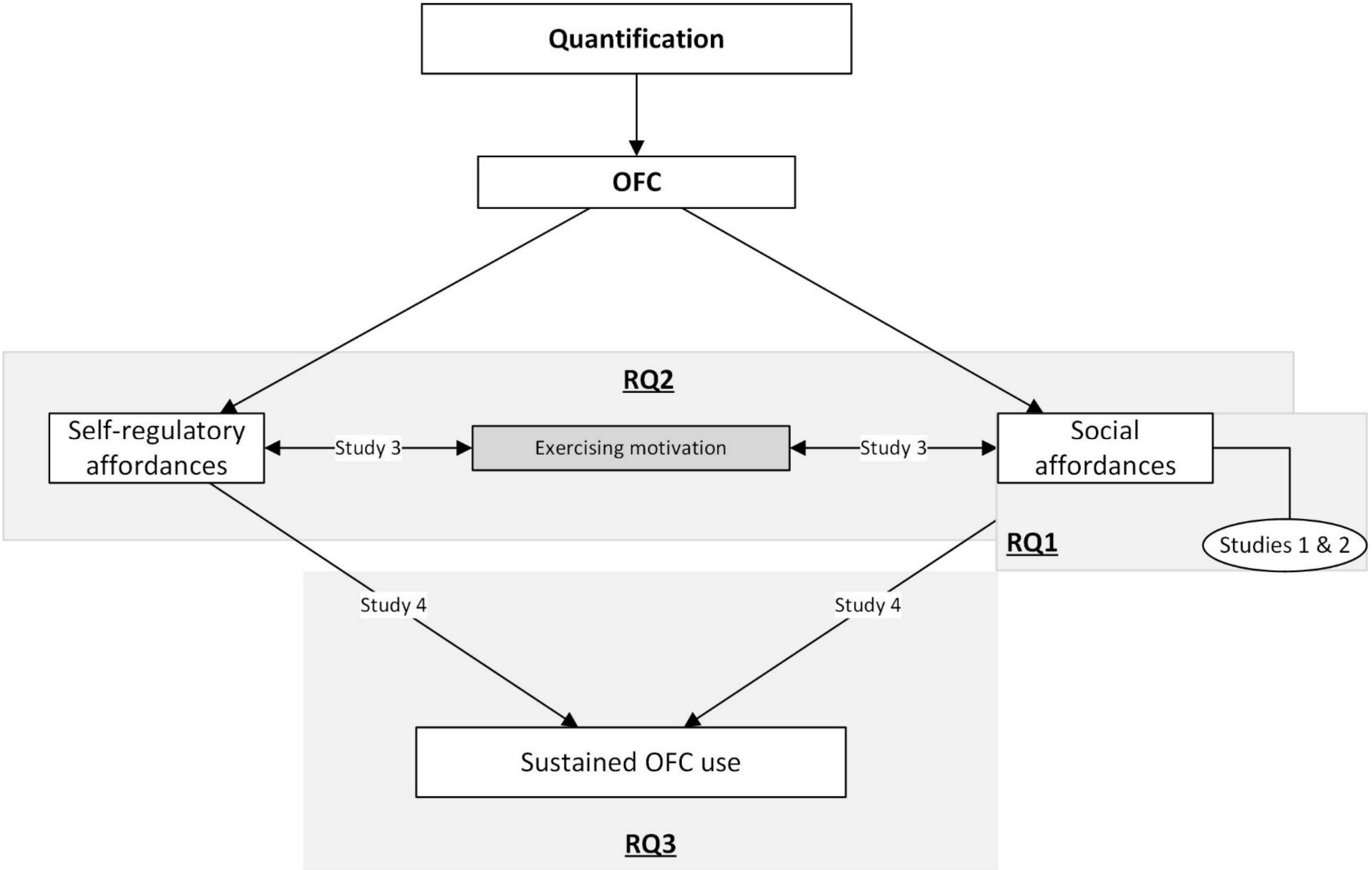

Figure 3 Theoretical framework of the dissertation with study outline

2 EMPIRICAL RESEARCH

INTRODUCTION

The objective of this doctoral thesis is to unravel the underlying reasons for continued OFC use. To answer the three main research questions of this thesis, four studies were conducted, presented in chapter five, six and seven. Each chapter is introduced with a brief section in which we contextualize the study within the theoretical framework of this thesis and the corresponding research questions. Chapter five presents the first two studies of this thesis. In studies 1 and 2, we focused on research question 1 (*What is the role of the social interaction that is afforded on OFCs?)*. We inquired the practice of giving recognition and social support for exercise behavior, shared on OFCs and social media. In Chapter six, we address research question 2 (*How are motivations for exercising linked to the affordances of OFCs*?) by means of study 3, which presents an empirical test of our theoretical framework on the interplay between motivations for exercising and self-regulatory and social affordances of OFCs. More particularly, the study illustrates how varying motivations for exercising are addressed and supported by the features offered in OFCs. Finally, in Chapter seven, to assess whether social affordances can play a major role in creating a sustained of OFCs (*RQ3)*, we present a cross-sectional study *(study 4)* that illustrates how OFC use shifts from being self-regulation centered in the beginning to a more socially oriented in the longer term. Table 1 presents an overview of the four studies.

Table 1.

Overview of the studies

Research question	Study	Title	Purpose	Methods	Status
RQ1. What is the role of the social interaction that is afforded on OFCs?	1	Computer-mediated social support for physical activity: a content analysis	To inquire the practice of giving recognition and social support exercise behavior, shared on OFCs and social media	Deductive content analysis, API based data collection	Published *Health Behavior & Education*
RQ1. What is the role of the social interaction that is afforded on OFCs?	2	Broadcast yourself: An exploratory study of sharing physical activity on social networking sites	To explore the motivations of sharing exercise behavior on social networking sites	Survey study, API based on-platform recruitment	Published *Media International Australia*
RQ2. How are motivations for exercising linked to the affordances of OFCs?	3	Matching Online Fitness Community Affordances to Running Motivations	To illustrate that varying motivations for exercising are addressed and supported by the features offered in OFCs	Survey study	In review *Behavior & Information Technology*
RQ3. Does social interaction lead to a sustained use of the platform?	4	Understanding persistence in the use of Online Fitness Communities: Comparing novice and experienced users	To demonstrate the potential of social affordances for sustained OFC use	Survey study, API based on-platform recruitment	Published *Computers in Human Behavior*

Before proceeding to these four studies that make up the core of the research presented in this thesis, we present a contextualizing chapter on our research object (OFCs) in which (1) we briefly touch upon the socio-demographics of users of online data analysis platforms (both OFCs and technology/brand-based) in Flanders, Belgium; and (2) we empirically match the characteristics of virtual communities to those of OFCs, in order assess to the (implicit) assumption that OFCs can in fact be considered virtual communities.

CHAPTER FOUR: ONLINE FITNESS COMMUNITIES AS VIRTUAL COMMUNITIES

1. Introduction

The concept of an OFC as a virtual community was described in Part one, Chapter two of this dissertation. OFCs were theoretically matched to the characteristics of virtual communities: *purpose, place, platform, population interaction structure and profit model.* In this chapter, we empirically assess the *place, platform* and *population interaction structure* characteristics of OFCs. We specifically focus on these three characteristics, as they describe how interaction between members, a key element within a virtual community, is organized. Three hypotheses were formulated:

H1: For OFCs, place is a hybrid concept, meaning that interactions between members take place both online and offline.

H2: Currently, communication in OFCs occurs largely asynchronous.

H3: The population interaction structure in OFCs can be considered a computer-supported social network.

We tested these hypotheses by drawing on several of our datasets, collected in our studies on OFC use. From 2012 until present, our research on OFC use has resulted in the production of five datasets that contain more data and information than we relied on for the 4 studies underpinning this dissertation. This information is nonetheless valuable as it provides us with detailed info on various aspects of OFC use in Flanders. Table 2 provides an overview of each dataset's topic, date and number of respondents.

Table 2.

Overview of the datasets of the dissertation

	Topic	Date	N	Sample
Dataset 1	Social support for exercise behavior in OFCs and SNS	2012	32.493 tweets and 2.161 Strava activities	International dataset
Dataset 2	Social tie strength on Strava	2014	327 Strava users	Dataset for Flanders, Belgium
Dataset 3	Strava and RunKeeper use	2014	434 Strava or 199 RunKeeper users	International dataset
Dataset 4	Sustained OFC use	2015	768 Strava users	International dataset
Dataset 5	OFC affordances and motivations	2016	360 OFC users	Dataset for Flanders, Belgium

2. Information on (online) data analysis platform users

Our most recent dataset (dataset 5) contains 360 Flemish runners who use an online data analysis platform such as RunKeeper or Strava[3]. The average user's age is 37 years (*SD*=10.05), the youngest runner in the dataset is 15 years old, the oldest is 63. 48% of the users in the sample are men, 52% are women. Differences in platform use were observed between men and women. RunKeeper, Runtastic, Nike+ and appear to be largely used by female runners whereas Strava, Polar Flow and Garmin Connect have more male users. Self-monitoring of activities is a common practice among users: 70% of the runners indicates to (practically) always upload their activities to their respective profile. The runners in dataset 5 average 2-3 runs per week. They mostly run alone (69%).

Dataset 4 (2015) only focused on cyclists (*N* = 768) using Strava. For this group, we saw a larger proportion of male users (97%) than for runners (72% in dataset 5)[4]. The average age of a cyclists on Strava is 38 years (*SD*=9.91), comparable to the average age in dataset 5. The youngest runner in the dataset is 15 years old, the oldest is 77. Eighty per cent of the Strava cyclists indicates to (practically) always upload their activities to Strava. The cyclists in the dataset average 3-4 rides per week.

3. H1: Place characteristics of OFCs – a hybrid concept

From a theoretical perspective, we demonstrated that virtual communities are to some extent linked to a *place* (Porter, 2004). Therefore, virtual communities can exist on two levels: either hybrid or exclusively virtual. A hybrid community implies that members can have interactions in both the physical and virtual world and as such makes the virtual community an extension of an 'offline' community or vice versa. On the other hand, an exclusively virtual community excludes physical in-person relationships between the community members. We

[3] Predifined list: RunKeeper – Strava – Endomondo - - Runtastic – MapMyRun - Nike+ - Google fit - Start 2 Run
Polar Flow - Garmin Connect - Adidas MiCoach - TomTom MySports – Movescount - Sport Tracker

[4] Dataset 6 was collected in 2015. As the user bases of OFCs evolve rapidly, this number may have dropped in favor of female cyclists.

argue that OFCs are hybrid communities. This assumption is based on insights from dataset 2 & 4, which contain information on the connections between Strava users.

Dataset 2 (2014) contained information on the closeness of the relationships between Strava members. As a part of the study, each research participant was presented with an overview of his/her list of Strava friends (i.e. the users they 'follow' on Strava) and prompted to indicate the closeness of their relationship with each contact. The main insights from this dataset are:

- The average Strava user follows 21 others (*SD*=14.5) (in 2014);
- On average, the respondents indicated to know 80% of their Strava friends in person. The other 20% are exclusively online connections;
- The participants consider 40% of their Strava friends to be 'close friends';
- Three quarters (75%) indicates to go exercising with at least one of their Strava friends in real life. On average, they go cycling with 43% of their Strava friends.

Dataset 4 (2015) contains self-reported data on the number of members people are following & are followed by on Strava, whether or not followers and persons followed know each other in person and whether or not they go cycling together in real life. These were the main insights gathered from this dataset:

- Strava users indicate that they follow 35 others users on average (*SD*=54.3) of which they claim to know 80% or more in person.
- Furthermore, they indicate to be followed by 31 others (*SD*=54.7). Here again they claim to know 80% or more of their followers in person.
- 80% of the Strava users claims to frequently go cycling with at least one of their Strava friends.
- 60% indicates to have frequent offline conversations about each other's activities after reading about them on Strava.

The insights from these datasets support our hypothesis that OFCs are hybrid communities in terms of virtualness. The offline relationships between the users indicate that OFCs can be considered an online extension of offline friendships, of which exercising is one of the components. Of course, this conclusion can only be drawn for Strava. Our assumption is however that the same conclusion holds for other OFCs as well. Further research is needed to confirm this however.

4. H2: Asynchronous communication in OFCs

Depending on the platform, a virtual community can afford (near)-synchronous, asynchronous or hybrid interaction. We hypothesized that interaction between members in OFCs is largely asynchronous, which implies that a time lag occurs between postings of activities and the interaction that arises around it, such as giving Kudos', which is the Strava equivalent of a 'Like' on Facebook, to each other's activities and comments. Accordingly, our datasets give us some insight into the extent to which asynchronous communication features are used.

From dataset 1 (2012), we know that on Strava, 79.8% of the Strava athletes got some form of social feedback to their activities. Of the activities that were collected, 59.6% received some form of social feedback[5] from other Strava members (Kudos, comments or both), 57.7% of the activities received one or more 'Kudos' and 21.3% received one or more comments.

Furthermore, from dataset 3 (2014), we know that Strava and RunKeeper users report to receive 'likes' and comments from other members. This is especially the case for Strava, where 66% of the members indicate to at least 'frequently'[6] receive likes for their activities. On RunKeeper, this is only 21%. Comments are less often provided: 34% of the Strava users reports to at least 'frequently' receive comments on their activities. For RunKeeper this is only 12%. This difference in frequency of interaction between OFCs is also clear from dataset 5 (2016). Taking all OFCs queried in dataset 5 into account, it appears that 25% of the OFC members indicate to give a 'like' to another member's activity 'frequently' or even more often. Eleven per cent frequently (or more often) gives a comment to another member's activity. Almost half of the OFC users never gives comments or 'likes'. This number, however, is significantly lower on Strava, where only 9% (!) indicates they never give a comment and 4% never gives a 'like' to

[5] Since the data date back to 2012 and the user base of Strava has increased in the past 5 years, is likely that to date, this number will be even higher.

[6] Measured on a 7 point Likert-scale: Never-Rarely-Occasionally-Sometimes-Frequently-Very often-Every time

another members activity. Indeed, compared to other OFCs, interaction seems significantly higher on Strava.

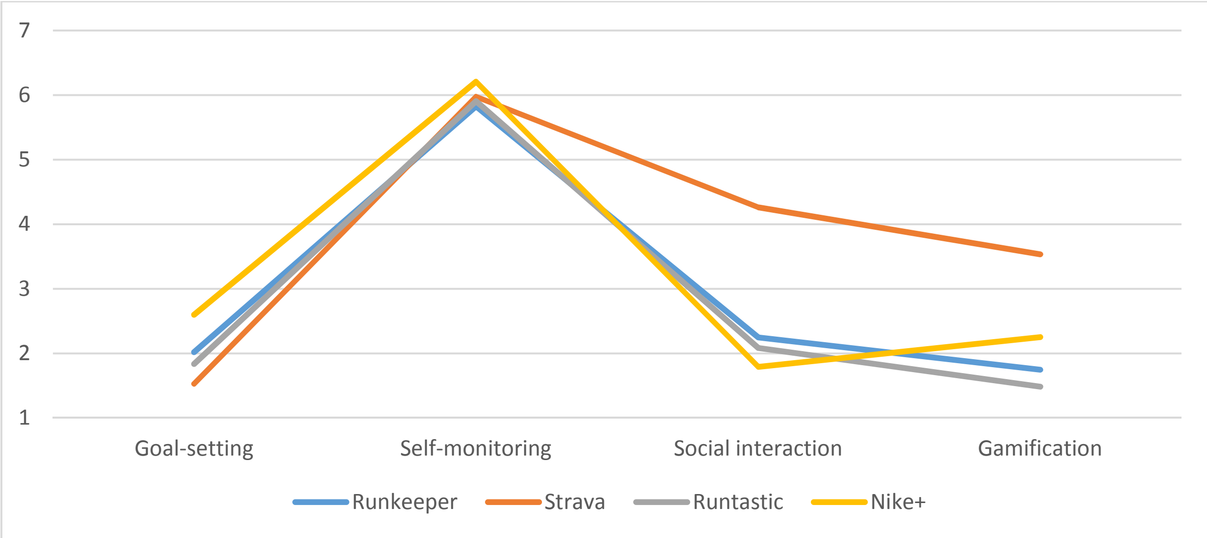

Figure 4 Feature category use in 4 OFCs (2016) (Usage of features on a 1 -7 Likert scale)

From these data, we can conclude that OFC members use the available features for asynchronous communication in OFCs and therefore we may conclude that asynchronous social interaction between members can be observed, although the use intensity of these features varies significantly, with Strava as a leading OFC in this regard.

5. H3: OFCs as networked interaction structures

The insights from the previous paragraphs also shed light on the population interaction structure of OFCs in general, and Strava in particular. In recap, according to Porter (2004), four types of population interaction structures in virtual communities can be distinguished: *(1) computer supported social networks* with either strong or weak ties among members emerging from (in)frequent supportive contact. Supportive behavior is typical in these networks*;* (2) *networked interaction structures*, in which community members are more loosely connected and socially & geographically dispersed. These networks generally have a more utilitarian function and membership is often of short duration; *(3) small groups* with close ties and frequent, strong (socially supportive) interaction, often marked by an exclusive membership; *(4) virtual publics* which are largely open (no password or login required) platforms with only limited interaction. Certain characteristics of *small groups* and *virtual publics*, such as exclusive membership and limited interaction, already lead us to conclude that OFCs cannot be considered either of the two.

Analysis of datasets 2 and 4 previously demonstrated a certain closeness of the relationships between Strava members with 40% of Strava friends being defined as 'close friends' (dataset 2) and 75% being an (occasional) exercise partner (dataset 2). This already led us to conclude that Strava is to be considered a hybrid concept as both online and offline interactions among members exist. Furthermore, the assessment of the platform type of OFCs, for which we concluded that *asynchronous communication* is most common, demonstrated that social feedback and supportive behavior is to a certain extent present in OFCs. Based on this information, namely (1) the presence of both strong and weak ties and (2) the presence of supportive behavior, we tend to categorize OFCs as *computer supported social networks.* We do believe however, that further (ethnographic) research and social network analysis is needed to further substantiate this claim.

6. Conclusion

The aim of this chapter was to empirically validate OFCs as virtual communities by means of available data on interaction and social tie structures in OFCs. The data indicate that in terms of *place*, *platform* and *population interaction structure*, OFCs can be described as virtual communities with a *hybrid place* concept, implying that (1) there is a link between the offline and online connection of its members; (2) that communication is largely *asynchronous;* and (3) *interaction structures* between members can be characterized as *networked interaction structures.* The data also indicate that the degree of interaction among OFC members differs significantly among existing OFCs, with Strava as the leading OFC in terms of interaction among members

CHAPTER FIVE: SOCIAL INTERACTION IN ONLINE FITNESS COMMUNITIES

1. Contextualization

In our theoretical framework, we distinguished both self-regulatory and social affordances as the main motivational affordances of OFCs. Social features enabling these social affordances have the potential to foster an OFC member's sense of belonging and relatedness and as such, lets him/her experience a connection to significant others. In brand-based platforms, these social affordances are oftentimes lacking, whereas OFCs tend to focus strongly on them.

This chapter specifically focuses on these social affordances in OFCs. We assume that encouragements for exercise behavior, received under the form of 'likes' and comments to the shared activities can strengthen people's sense of competence (Murcia et al., 2008). After all, we know that social interaction, and more particularly social support, is important to keep people motivated to be physically active. When people are increasingly connected to each other in online social networks, social support for exercise behavior, while traditionally considered from an "offline" perspective, could now equally be provided and received online. OFCs have tapped into this potential and enable social affordances through their social interaction features. To date, however, the practice of providing and receiving online social support for exercise behavior, has received little academic attention. Hence, this chapter aims to lay-out the use of these features and as such addresses the first research question of this thesis: *What is the role of the social interaction that is afforded on OFCs?*

In this chapter, we want to asses if people can (and do) provide and receive online social support for their exercise behavior through the use of OFCs. Two studies were designed and conducted to substantiate this hypothesis.

Study 1: Computer-Mediated Social Support for Physical Activity: A Content Analysis

The first study investigates the practice and nature of providing online social support for exercise behavior. In OFCs, users usually have three basic features available to interact upon each other's activities: (1) a 'like' button, (2) commenting on the activity and (3) sharing the activity on external online social networks (e.g. Facebook). On the latter external networks, the first two features are available as well and as such, non-members of the OFC can also interact on the activity. With this study, we aim to demonstrate that OFCs are a channel to provide and receive online social support for exercise behavior. To that end, we investigate which types of social support are provided through the use of the above features, both in the OFC and on external social networks.

This study used a qualitative approach to assess online social support for exercise behavior. In the study, a deductive content analysis is applied to a large dataset of replies given to physical activities shared in either an OFC or on Twitter, in attempt to 1) assess if online social support is provided to PA on OFCs and social media; and 2) distinguish the types of social support that can be found. This study contributes to the objective of this thesis as it demonstrates how online social support, especially in the form of recognition for completion of PA, can be expected when using an OFC.

Study 2: Broadcast Yourself: an Exploratory Study of Sharing Physical Activity on Social Networking Sites

Given the outcomes of the first study, we considered it important to further investigate the practice of sharing activities outside of the OFC, on external social networks as Facebook and Twitter. Via mainstream social media, athletes can reach a larger online audience and as such enlarge their exposure (Hamari & Koivisto, 2013). This exposure can increase the amount of feedback that is received for the activities that are being shared. The question that rises here is what drives people to share their activities on for example Facebook or Twitter? Therefore, this second study aimed to reveal the motivations for sharing physical activities on online social networks (outside of the OFCs).

This study used a quantitative approach. An online survey was conducted among Strava users who share their activities on Twitter. We tested a SEM model to demonstrate the motivations to share exercise behavior on social media. SEM is an applied statistical technique that allows to test the goodness-of-fit of a hypothetical model to a measurement model, based on data collected through for example quantitative surveying. In an SEM model, assumptions about the strength of hypothesized relationships between indicator variables (both manifest and latent) are tested. Study 2 contributes to the objective of this thesis as it demonstrates how OFCs, through sharing PA on social media can let users experience basic needs satisfaction of relatedness and competence.

Study I: Computer-Mediated Social Support for Physical Activity: A Content Analysis

Health Education & Behavior – *In Press*

Jeroen Stragier, Peter Mechant, Lieven De Marez & Greet Cardon

Abstract

Purpose: Online Fitness Communities are a recent phenomenon experiencing growing user bases. They can be considered as online social networks in which recording, monitoring and sharing of physical activity (PA) are the most prevalent practices. They have added a new dimension to the social experience of PA in which online peers function as virtual physical activity partners or supporters. However, research into seeking and receiving computer-mediated social support for physical activity is scarce. Our aim was to study to what extent using Online Fitness Communities and sharing physical activities with online social networks results in receiving various types of online social support. Method: Two databases, one containing physical activities logged with Strava and one containing physical activities logged with RunKeeper and shared on Twitter were investigated for occurrence and type of social support, by means of a deductive content analysis. Results: Results indicate that support delivered through Twitter is not particularly extensive. On Strava, social support is significantly more prevalent. Especially esteem support, expressed as compliments for the accomplishment of an activity, is provided on both Strava and Twitter. Conclusion: The results demonstrate that social media have potential as a platform used for providing social support for PA, but differences among various social network sites can be substantial. Especially esteem support can be expected, in contrast to online health communities, where information support is more common.

Keywords

Online fitness community, computer-mediated communication, social media, physical activity, exercise behavior, e&mHealth

1. Introduction

Technological developments such as the internet, social media and mobile devices have introduced the possibility to seek and receive social support in a computer-mediated environment. An extensive body of research exists on the beneficial effects of computer-mediated support groups for various physical and psychological health issues. However, research into seeking and receiving computer-mediated social support for physical activity (PA) is somewhat less available.

Traditionally, friends, family and significant others are considered as the most predominant sources of social support for PA (Anderssen & Wold, 1992; Dahlem, Zimet, & Walker, 1991; Prochaska, Rodgers, & Sallis, 2002; Reyes Fernández, B., Montenegro Montenegro, E., Knoll, N., & Schwarzer, R., 2014). Different types of social support can be provided by different sources, and can differ according to whom the support is intended for. For adherence to an exercise regimen, family support and support from important others such as colleagues and physicians are considered to be an important source of social influence and determining for PA adherence and compliance (Beets, Cardinal, & Alderman, 2010).

Social support as an umbrella phrase captures both support perceptions (perceived support) and receipt of supportive behavior (received support). Perceived support has been more prominently linked to health as compared to received support with researchers offering differing assessments of the strength of the received-perceived support relationship (Haber, Cohen, Lucas, & Baltes, 2007). The relationship between received social support and health appears more indirect. E.g. Luszczynska et al. (2007) indicated that received social support positively influenced adherence to antiretroviral medication through its positive effect on self-efficacy. In this article, the emphasis lies received support or the quantity of supportive behavior received by an individual.

Substantial research exists on practices of social support in online health communities, defined as online environments in which users interact with one another around a set of common interests or shared purpose related to health (Newman, Lauterbach, Munson, Resnick, & Morris, 2011). Winzelberg (1997) analyzed 306 messages posted in an eating disorder electronic support group. He concluded that requests for informational support and provision of emotional support were most common. Using a thematic deductive analysis, Coulson (2005) categorized 572 messages, posted in a computer-mediated support group for people living with irritable bowel syndrome, into the 5 main categories of social support defined by Cutrona (1992). Information support appeared to be the primary type of social support that was being provided.

The potential of online social networking for health promotion is increasingly acknowledged (Balatsoukas, Kennedy, Buchan, Powell, & Ainsworth, 2015; Maher et al., 2014; Vandelanotte & Maher, 2015; Williams, Hamm, Shulhan, Vandermeer, & Hartling, 2014). Cobb (2012) argues that Facebook offers significant opportunities to intervention designers due to its social network connection that affords both large scale diffusion and social support. Cavallo et al. (2012) used Facebook in an intervention study attempting to enhance social support for physical activity. Although they did not find a greater perception of social support between intervention and control group, it is argued that further use of online social networks in health promotion should be investigated.

Online Fitness Communities (OFCs), e.g. RunKeeper, Strava, Endomondo, and MapMyRun, are a recent phenomenon that experienced growing user numbers in recent years (Delaney, 2013; Dredge, 2013, September 23). On these platforms, results of exercise sessions or other physical activities can be uploaded. This mostly involves running, cycling and walking, but uploading other activities including swimming, skiing or skating is also common (Stragier, Mechant & De Marez, 2013). This enables the users to monitor their progress on their personal profile page. Furthermore, the platform enables social interaction among users by means of goalsetting, joining groups and sharing activities with others. Twitter and Facebook users can also share their activities with their Facebook friends or followers on Twitter.

The possibility to share PA with online peers adds a potentially new angle to the social dimension of PA, which has been considered traditionally from a face-to-face perspective, pointing to friends, family and peers as the most important sources of social support for PA. The role of friends and followers on online social media has not been addressed to date, although often this has become the principal platform for internet users to share information. Therefore, the aim of our research is to investigate the occurrence and nature of online social support for physical activity.

In this article, the emphasis lies on social feedback provided to PA shared on social media. More specifically, the extent to which this social feedback contains certain types of social support is investigated. First, we will verify to what extent social feedback is provided to 1) physical activities posted in an OFC (Strava) and 2) activities logged with RunKeeper and shared on a social network site (Twitter). Second, we want to know what types of supportive messages are provided in the feedback.

2. Methods

Data collection

Data were collected from RunKeeper, Strava and Twitter. RunKeeper, one of the most popular OFCs, has 50 million users in 2016 (“Fitness app RunKeeper wants to be a retailer”, 2016). It is used for logging a wide variety of activities of which running, cycling and walking are most prevalent. Strava is an OFC which mainly focuses on leisure time PA, especially cycling and running. The latest figures on the Strava user base suggest 10 million users ("A VC Lets a Bet Ride: the Story of Strava," 2013) generating 2 million activities per week ("A Global Data Set," 2014). It was opted to use the OFCs Strava and RunKeeper for their large user bases and frequent listing among popular health and fitness tracking apps.

Founded in October 2006, Twitter serves as an outlet for a user’s thoughts and opinions, expressed in status reports or ‘tweets’ of maximum 140 characters. These tweets are either public and visible to all, or private and visible only to the Twitter user’s ‘audience’, who in Twitter terms are named ‘followers’. Followers have the opportunity to respond to tweets using @replies, which are comments or reactions that can be posted on a tweet; they can ‘favorite’ a status, which means they can indicate to like or appreciate the tweet; and they can ‘retweet’ a status. Retweeting implies that a follower in turn shares the tweet with his/her followers.

An example of a PA report on Twitter is presented in Figure 1. It reports on the completion of a marathon by a RunKeeper user (‘Just completed a 26.20 mi run’). Furthermore, the tweet contains a personal reflection of the runner on the activity (‘First marathon under my belt. Boom!), a short URL that redirects to the RunKeeper platform on which further data of the activity, such as speed, time and trajectory, can be accessed (http://rnkpr.com...) and the hashtag #RunKeeper. Furthermore, Figure 1 illustrates that the tweet got ‘favorited’ 4 times, ‘retweeted’ once and received 3 ‘@replies’.

Figure 1 Example of a RunKeeper Activity Tweet

Two datasets were collected. One dataset contained 33,908 tweets with the hashtag #RunKeeper that reported on the completion of PA from May 4th until July 2nd 2013. The other dataset consisted of 2,161 Strava activities. It was opted to use activities from both Strava and RunKeeper to ensure a broader data collection beyond activities collected with only one OFC. Data from one of the OFCs was extracted from Twitter. In doing so, it was possible to observe potential differences in social support provided directly on an OFC (Strava in this case) and in second instance, shared outside the OFC on a social network site, in this case, Twitter.

The database containing tweets with the hashtag #RunKeeper was created using a custom PHP script that interacted with the Twitter Application Programming Interface (API) function GET search/tweets ("GET search/tweets," 2013). Particularly interest was placed in the expressions of social support that are given to the tweet, for which the amount of favorites, retweets and @replies were considered. Therefore, starting on August 2nd 2013, the Twitter API was used again to collect the number of retweets and favorites of the original tweets. This could be achieved for 32,493 of the initial 33,908 tweets. The remaining 1,415 were no longer retrievable due to deletion of the tweet, the closing of the corresponding Twitter account or the change from a public to a protected account. This might point to increasing privacy awareness of some Twitter users. After all, Twitter users are tweeting to a largely invisible, "unseen" (Scheidt, 2006), or "imagined" audience (Marwick & Boyd, 2011). Moreover, in the absence of a clear-cut communication context, they might be confronted with trolling and harassment.

A custom PHP script was used to collect all @replies for the given tweet. The end result was a database of 32,493 tweets, from 18,991 Twitter users, containing per tweet the number of favorites, retweets and all the @replies.

The database containing the Strava activities was collected using the Strava API in June 2014. First, a random sample of Strava athletes was asked for their cooperation in our research. These athletes were asked for consent to use their Strava data. When granted, random activities of these Strava users (N=206) were downloaded using the Strava API. For each of the 2,161 activities, all comments and kudos were collected as well. Figure 2 demonstrates the data collection process.

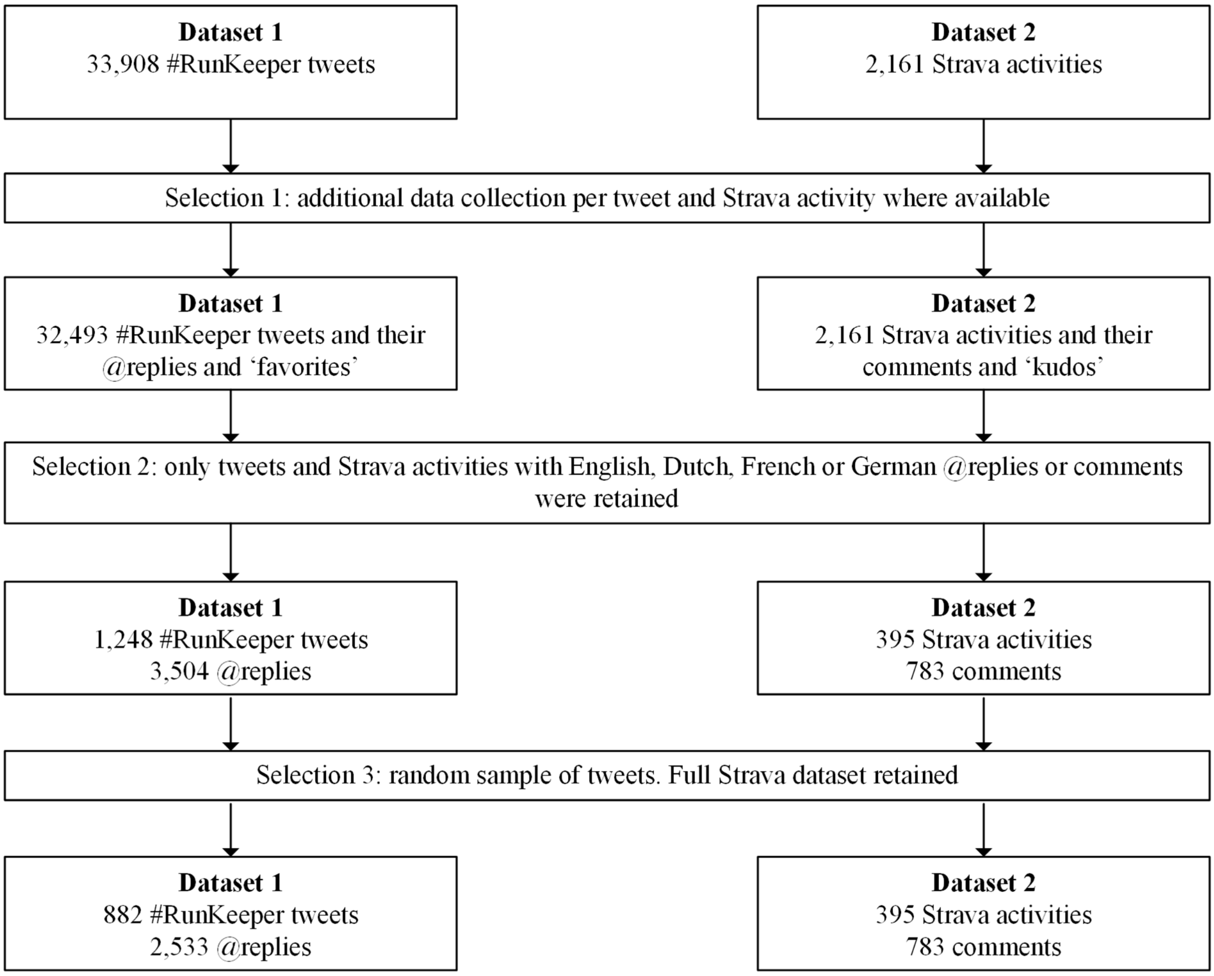

Figure 2. Data selection process.

Data analysis

Descriptive quantitative statistical analysis was applied to assess the amount of social feedback that was provided to activities posted on Strava and RunKeeper activities shared on Twitter respectively. To assess the nature of social support provided in Strava comments and Twitter @replies, a deductive content analysis was applied. Content analysis is a systematic method used to analyze written, verbal and visual communication messages (Cole, 1988). This method is frequently applied in social sciences. The aim is to describe a phenomenon as thoroughly as possible by means of summarizing the phenomenon into concepts and categories (Elo & Kyngäs, 2008). Content analysis can be either inductive or deductive. An inductive research approach is mostly used when insufficient knowledge from prior or existing research is available. In deductive content analysis, the analysis is based on existing theory and applied to new data. Deductive analysis starts with selecting the unit of analysis, in our case, the comments received on Twitter and Strava. Next, a theory based categorization matrix is developed and the units are coded into categories. In our study, a deductive content analysis was used.

The analysis departed from Cutrona's & Suhr's (1992) typology of social support as used by Braithwaite et al. (1999), depicted in table 1. The typology has 5 main categories: *information support*, *tangible assistance*, *network support*, *esteem support* and *emotional support*, each with their own subcategories. All comments that inquire the poster to his experience of the activity or future goals were categorized under a new category labeled '*Showing interest*'.

Table 1

Typology of social support used in the analysis

Categories	Subcategories
Information support	Advice, referral to experts, situational appraisal, teaching
Tangible assistance	Loan, perform direct task, perform indirect task
Network support	Access, presence, companions
Esteem support	Compliment, relieve of blame, validation
Emotional support	Relationship, physical affection, confidentiality, sympathy, understanding or empathy, encouragement, prayer

For the activities shared on Twitter, a new database was created containing only those activities that received one or more @replies. This resulted in a database of 1,787 original activity tweets that received 5,226 @replies. Second, this number of @replies was reduced by selecting only those tweets with @replies written in languages understood by the researchers (English, Dutch, German or French), leaving 1,248 original tweets and 3,504 accompanying @replies. A random sample of 882 activities, with 2,533 accompanying @replies was retained for analysis.

For Strava, all of the activities that received comments (N=395) were retained. The number of comments posted to these activities was 1,198. Similar to the tweets, only those activities with comments posted in English, Dutch, German or French were selected, which resulted in 783 comments retained for content analysis.

Two researchers independently coded the @replies and comments. One researcher coded the full sample of @replies (N=2,533) and Strava comments (N=783), the other researcher coded a random subsample of 1,000 @replies and all of the Strava comments. Cohen's Kappa was used to calculate intercoder reliability. Since tweets and comments could be assigned to multiple categories, Kappa was calculated for each category separately. For all categories, Kappa reached satisfactory values above .65, indicating a considerable similarity between the codes assigned by both researchers. In order to settle the coding differences, a 'judge' was used (a non-involved researcher) to decide upon labels that both coders could not agree on.

3. Results

Presence of social feedback

For Twitter, 6.8% of the 32,493 activities received some form of social feedback. 3.2% received at least one 'favorite', 0.6% got 'retweeted' once or more and 5.5% received at least one @reply. Aggregating the tweets per Twitter user shows that 10.3% of the Twitter users whose activities were collected got some form of social feedback on one or more of their activities.

On Strava 59.6% of the activities that were collected received some form of social feedback. 57.7% received one or more 'kudos', 21.3% received one or more comments. 79.8% of the Strava athletes got some form of social feedback to their activities. However, the question remained to what extent the @replies and comments were containing some form of social support.

Types of social support

Further analysis of the @replies and comments provided more insight into the presence and types of social support. Table 2 shows the results of the deductive content analysis. For Twitter, 51.3% of the replies were labeled 'no support'. These replies did not contain any kind of social support as defined by the categories in our theoretical framework. Issues that are observed in these replies are e.g. discussions about malfunctioning of the app, making plans to go out for drinks, joking about the activity and describing the purchase of new equipment. On Strava, 43% of the comments did not contain any type of social support.

Table 2

Social Support in @replies and Comments (in %)

Type	Twitter	Strava
Esteem support	28.9	32.9
Compliment	28.9	32.8
Access	0.0	0.1
Information support	2.1	2.3
Advice	2.1	2.3
Emotional support	4.2	3.8
Encouragement	2.2	1.0
Sympathy	1.3	2.7
Relationship	0.5	1.1
Physical affection	0.2	0.0
Tangible assistance	0.6	2.8
Activity part-taking	0.6	2.7
Perform direct task	0.0	0.1
No support	51.3	43
Gratitude	9.6	9.1
Showing interest	7.8	9.7
Total	104.5	104.6
N	2533	782

9.6% of the @replies was labeled as 'gratitude'. As the category label suggests, these replies are expressions of gratitude in response to other @replies. The assigned label 'gratitude' grants some insight in individuals' support perceptions (perceived support) and demonstrates the individuals' awareness when receiving supportive feedback. 91% of these 'gratitude-replies' came from the poster of the activity tweet. The other 9% was posted by repliers who, in their turn, received some form of social support from the poster of the activity tweet. @replies from followers are often replied to by the poster of the activity. In fact, 40% of the @replies to an activity came from the poster of the activity him/herself, as a reaction to the other replies. 22% of the poster's replies are expressions of gratitude for support. Furthermore, they often also express support to their repliers. For example, to the activity:

Just posted a 3.61 km run - Great run tonight. Still some soreness, but adjusting. http://t.co/ixxx #RunKeeper,

One follower replied:

@xxx you did awesome!! Thanks for keeping me motivated :).

The original poster replied back with:

@yyy You did awesome too! Don't give up, and keep smiling.

For Strava, 9.1% of the comments were labeled 'gratitude'. 81.7% of the coded 'gratitude' comments came from the poster of the activity.

On Twitter, 43.6% of the @replies contained social support from one or more of the categories in the theoretical framework. On Strava, this was 51%.

Esteem support, expressed as compliments for the activity, appeared to be the most prevailing type of support. 28.9% of the @replies contained some compliment to the poster of the activity. Examples include: 'Congratulations', 'Nice one!' and 'Great job'. For Strava, esteem support was most prevailing as well, occurring in 33% of the comments.

Information support was found in 2.1% of the @replies. 'Advice' was the only category occurring under information support. Generally, advice is given on injury prevention, equipment, potential races etc., often as a reaction to the personal reflection of the poster of the activity. E.g. the activity:

Just completed a 6.19 mi run - Lots of hills today! Calf pain still, must have pulled something http://t.co/xxx #RunKeeper got the following reply:

@hxxx I had that issue a little while ago. I did more pre and post stretching. Seems to have helped.

On Strava, a similar amount of advice (2.1%) was given in the comments.

Four subcategories of emotional support were found in the @replies and comments. ‘Encouragements’ were the most prominent subcategory on Twitter (2.2%). Encouragements are those expressions stated in the @replies that were aimed at encouraging the poster to keep up their activities. Examples of these encouragements are: ‘Keep practicing!’, ‘You can do it! I believe’ and ‘Keep it up, you'll get there’. 1% of the Strava comments contained encouragements. ‘Expressions of sympathy’ is a second subcategory. These were found in 1.3% of the @replies and 2.7% of the Strava comments. This sympathy was expressed when a poster reported on a positive or negative experience during the activity. E.g. the Strava activity named:

Spindletop spin, crash at mile 70

got the following replies:

oh no. hope you're ok?

Sorry to hear about the bike and helmet.:). Body will heal.... Glad to hear you’re ok.

‘Relational support’ refers to expressions of love and relational closeness (Braithwaite et al., 1999), e.g. ‘*how are you doing my dear? Missing you xx get well soon xx*’. This subcategory was only present in the data to a limited degree on both Twitter (0.5%) and Strava (1.1%). ‘Physical affection’, expressed verbally, was found in only 0.2% of the @replies and not in the Strava comments. These are a verbal translation of physical expression of affection, e.g. ‘*HUG*’.

Tangible assistance was defined as the offering of concrete support to the poster of the activity (Braithwaite et al., 1999). In the data, this generally translated into offering to start exercising together. This was more common on Strava (2.7%) than on Twitter (0.6%).

'Showing interest', a category which was added to the existing framework, classifies all @replies and comments of followers that contained some form of question or remark regarding the activity addressed to the poster. 7.8% of the @replies contained this type of remarks. For Strava, this was 9.7%. An example of such a reply was addressed to the following activity:

Just completed a 6.28 mi run - 2 mile struggle then a very easy run. http://t.co/SWxxx #RunKeeper

The reply stated:

@DxxPxx What race are you preparing for?

4. Discussion and conclusion

This study provided a detailed insight in the amount and types of online support one can expect when posting an exercising activity to either an OFC or a social network site. Twitter and Strava were taken as case studies for our analysis. Social support on Twitter was defined by either receiving 'favorites, 'retweets' or @replies that contained social support. For Strava, receiving 'kudos' or comments containing social support were considered social support. On Twitter, social support was noticeably less prevalent compared to Strava.

From the content analysis, it was clear that 'esteem support' is by far the most prevalent type of social support on both Twitter and Strava. The prevalence of 'esteem support' in OFCs, compared to 'information support' being more common in online health communities (Coulson, 2005; Winzelberg, 1997; Winzelberg et al., 2003), demonstrates the difference between the two types of online communities in terms of type of received support. When designing effective interventions, this difference should be taken into account. Integration of characteristics of both community types could result in a more complete and effective intervention, through a broader social support provision.

Receiving social support has been linked with improved adherence to health behavior programs (Luszczynska, Sarkar, & Knoll, 2007). Our results illustrate what one can expected from social media in terms of receiving online social support for PA. With only 6.8% of the #RunKeeper activities on Twitter receiving some form of social feedback, it may seem that this is rather limited. This can largely be attributed to the affordances of Twitter. It can be assumed that performing the same analysis on e.g. Facebook will yield different results, as was also suggested by Cavallo (2012). Facebook is a social network site that is characterized by higher interactivity and closer friendship relations than Twitter (Hughes, Rowe, Batey, & Lee, 2012). Twitter on the other hand, provides its users with a higher level of anonymity. Unfortunately, accessing similar data on Facebook is not as straightforward as it is on Twitter due to the closed nature of Facebook accounts. Further research should apply a similar methodology to look into sharing physical activity on Facebook and the occurrence of social support from Facebook friends.

This study provides an innovative approach on how social support for PA occurs in online social media. However, some limitations of our study should be noted. First, as already stated above, only Twitter was used as a case study for social network sites. Twitter has its specific affordances and it is likely that the amount and type of social support is different on other social network sites such as Facebook. Second, tweets with hashtag #RunKeeper were used to illustrate the occurrence of social support on social network sites. It might have been an option to use #Strava tweets, to allow better comparability between on and off-platform feedback. However, we believe that using different platforms can improve the generalizability of the results. Third, while emphasis was placed on the message that is shared on social media, it would have been interesting to provide more information on the OFC user who shares his/her physical activity. Relating social network size to the amount of received support would be an interesting analysis and provide further insight on the importance of online social networking in designing interventions. The share of physical activity related status updates in the total number of statuses could deliver insights into the frequency of sharing.

Further research into online social support and health behavior could build on the methodology and results at hand. Our research focused on PA, but our methodology is applicable to several other fields of health behavior research, such as nutrition. Many OFCs exist that focus on tracking of food intake or weight loss (Mateo, Granado-Font, Ferré-Grau, & Montaña-Carreras, 2015). It would be most interesting to see our methodology applied to this field. Furthermore, research should look into the potential effect of receiving certain types of online social support and actual adherence to PA programs. The increasing popularity of wearable activity trackers such as FitBit, Jawbone and Moves also provides opportunities for research into PA as their easily accessible APIs are excellent tools for data collection and analysis. As indicated above, the results of this study may not be automatically generalizable to other social networks such as Facebook, due to the specific nature of Twitter. The same methodology applied to Facebook may yield very different results. Lastly, future research should evaluate if receiving online social support effectively leads to increase in physical activity or better adherence to physical activity programs.

The results can also be of good use to practitioners. In promoting physical activity, using OFCs could be recommended in order to assist e.g. novice runners in their efforts. By using OFCs, users not only get the opportunity to monitor their progress, they can also expect experiencing social interaction with online peers and receiving social support, whether in the OFC or through sharing activities on external social media. Furthermore, integrating OFCs and social media into promotional programs for physical activity may help adherence to the program.

In conclusion, social media may be a good platform for receiving online social support for PA, although our results indicate that dedicated OFCs such as Strava, where users share a similar interest and engagement in physical activity, will result in more social interaction and support. Furthermore, the difference in social support on Twitter compared to Strava, suggests that the better users are acquainted, the more interaction and thus support can be expected. When designing interventions, these elements should be taken into account. The growing popularity of OFCs as RunKeeper and Strava illustrates the value of their social networking element.

Study II: Broadcast Yourself: an Exploratory Study of Sharing Physical Activity on Social Networking Sites

Media International Australia – *Published (Adapted for this thesis) (2015)*

Jeroen Stragier, Tom Evens & Peter Mechant

Abstract

This paper focuses on the practice of self-tracking of physical activity data and sharing it via social networking sites. The use of wearable technology and smartphones with built-in GPS tracking technology, adequately capturing speed, distance and duration of physical activities such as running and cycling, are a lively example of the trend toward quantifying sports performances. The study explores the determinants and motivations of recreational athletes to share physical activity status updates on the social networking sites Facebook and Twitter. Evidence is drawn from a large-scale survey recruiting users of Strava, a popular Online Fitness Community. The results suggest that intrinsic motivations, rather than extrinsic motivations, determine a person's willingness to share physical activity via social networking sites.

Keywords

Social networking sites, online fitness communities, physical activity, sharing, motivations

1. Introduction

'Just completed a 9.23 km run' is an example of a frequently shared status update on Facebook or Twitter. It represents the sharing of personal physical activity of mostly recreational athletes via social networking sites. In doing so, athletes inform their online social network about their attempts to maintain a healthy life style or achieve athletic goals. The emergence of wearable devices that allow tracking of sports activities through GPS and accelerometer technology has provided recreational athletes with an improved means of self-monitoring their physical activity.

In recent years, various applications like Strava, RunKeeper and Endomondo that facilitate this type of physical activity tracking have experienced growing popularity and become ever prominent in people's sports experience participation. Such fitness apps not only allow athletes to collect data, but also to upload the data to a personal online profile that is connected to the application, and share the data with fellow athletes, fans and/or followers. These Online Fitness Communities (OFCs) support interaction with other athletes. In addition to on-platform interaction, these apps enable users to share their performances, progress and achievements with online peers on social networking sites like Facebook and Twitter. Hence, people have the opportunity to compare each other's fitness data via online and mobile technology. Research relating to mobile applications and social networking sites is growing (Danah Boyd & Ellison, 2007), but people's motivations to share their own physical activity with their peers remain largely a blank spot in academic research.

Taking the growing popularity of OFCs in running and cycling communities, our contribution focuses on the role of social networks in the expanding media sports ecosystem. Being an emerging site of innovation in media sport, social networks open up completely new fields of sports consumption and experience, and impact the way and intensity in which people practice sports (Kassing & Sanderson, 2010). OFCs, such as Strava, are a great example of how consumers and sports lovers share and create content being consumed in a social context and, hence, shape the digital media sports market. In order to gain insights into the development of OFCs and elaborate our understanding of the processes of sharing and consuming status updates, our research attention goes to the determinants and motivations of recreational athletes to share physical activity status updates with peer and fellow athletes on social networking sites Facebook and Twitter. Evidence is drawn is from a large-scale survey recruiting users of Strava, a popular OFC and application. The results will help in understanding the emerging practice of sharing physical activity using social networks.

2. Literature review

Self-monitoring of physical activity

Self-monitoring, also known under terms like self-tracking and 'Quantified Self', is the practice of keeping a log of various (physiological) parameters with the purpose of further analysis and obtaining insights about oneself (Barrett, Humblet, Hiatt, & Adler, 2013; Lupton, 2013; Nafus & Sherman, 2014; Swan, 2013). Self-monitoring is not a new phenomenon. People have always been tracking one or more aspects of their daily life of which weight might be the most prevailing. Diary keeping can also be considered as a way of self-monitoring. Quantified Self can be situated within the 'Internet of Things' which refers to the increased embedding of microprocessors and sensors into everyday artefacts and practices. In recent years, the upcoming of wireless and mobile sensor technology has offered improved opportunities for self-monitoring by means of automated data collection and improved analysis and visualization (Lupton, 2013).

One of the most prominent domains of Quantified Self is physical activity (Lupton, 2013). Physical activity is defined as: 'any bodily movement produced by skeletal muscles that requires energy expenditure' (WHO, 2015), and has shown to be essential in the prevention of inactivity related health issues including cardiovascular diseases and depression. Especially regular moderate intensity physical activity, for example as walking, running, cycling have significant health benefits. As self-tracking often stimulates self-management and improvement (Aittasalo, Miilunpalo, Kukkonen-Harjula, & Pasanen, 2006), technology can be a means of stimulating physical activity. The latest smartphones with built-in GPS tracking technology adequately capture speed, distance and duration of physical activities such as running and cycling are a lively example of this trend toward quantifying sports performances. The growing popularity of wearables like Fitbit and Polar loop reinforces this trend. In line with the increased adoption of these technologies, OFCs, designed to analyze self-monitored data and share results with online peers are experiencing a growing uptake (Delaney, 2013; Lafferty, 2013).

In this article we focus on the use of Strava, a community platform launched in 2011, now having over 10 million users generating 2 million activities per week ("A Global Data Set," 2014; "A VC Lets a Bet Ride: the Story of Strava," 2013). Strava can be categorized as an OFC, situated in a larger scheme of web-based social media platforms, comprising for example blogs, social network sites as Facebook, wikis, media-sharing sites as Flickr or Youtube (Kietzmann, Hermkens, McCarthy, & Silvestre, 2011). It serves a specific audience consisting of recreational and (semi)-professional athletes and allows them to self-monitor their physical activity and share it with their online peers.

With Strava, users can manually add activities to the online platform or upload sessions logged through wearable devices such as smartphones or dedicated sports watches. Depending on their hardware specifications, these wearables can log various environmental and physiological parameters including time spent exercising, distance covered, average speed/pace, heart rate and power output. After completion of the activity, the data is transferred to their user profile on the Strava platform, where the users can analyze their performance. Users can join Strava with a free account or can opt for a paid premium account, which allows them to use more features of the platform. Strava, along with other similar platforms, also connects athletes, both recreational and professional. Users can view other athlete's activities and allow others to view theirs. Furthermore, users can interact with others based on the activities they share. On Strava, they can give 'Kudos', which is the Strava equivalent of a Facebook 'like', to activities posted by a Strava user as a means of endorsing each other for their achievements, and/or comment the activity. Lastly, and of main interest in this study, users can share their activities on their Facebook or Twitter profile.

Social network sites (SNS) like Facebook and Twitter are omnipresent and widely used. Boyd & Ellison (2007) define SNS as 'web-based services that allow individuals to (1) construct a public or semi-public profile within a bounded system, (2) articulate a list of other users with whom they share a connection, and (3) view and traverse their list of connections and those made by others within the system'. In our research, we focused on the use of Twitter and Facebook for sharing physical activities logged with Strava. Facebook is regarded as a typical

SNS, but Twitter, which has a number of typical social network elements that meet Boyd & Ellison's (2007) definition of a social networking site, also differs from a typical SNS because users are not obliged to ask permission to follow other users, unless it concerns a closed account (Danah Boyd, Golder, & Lotan, 2010). Nevertheless, for this study we will consider both entities to be SNS. Using SNS for sharing information with peers is common practice and many forms of sharing on social networking sites have been investigated (e.g. Acquisti & Gross, 2006; John, 2012; Qiu, Lin, & Leung, 2013). Convenience, entertainment, passing time, interpersonal utility, control and promoting work appear to be the main motivations for sharing links on Facebook (Baek, Holton, Harp, & Yaschur, 2011). Regarding sharing of health data in online communities, Wicks et al. (2010) state that sharing health data on PatientsLikeMe, a platform dedicated to help patients of certain illnesses to find people with the same condition as theirs to discuss and find solutions, may benefit patients through engaging in conversations which can help them to self-manage their condition. Their results indicated that users of the platform benefited from the social functions of the platform, especially those suffering from with mood disorders, making them require less inpatient care. Sharing of physical activities however, has not been thoroughly addressed to date.

Self-determination theory

For the purpose of our study, we would like to introduce self-determination theory (SDT), an established framework in motivations research, applied in various research fields as health behavior, education and health care (Deci & Ryan, 1975, 1985, 2010). SDT departs from intrinsic and extrinsic motivations as the driving forces behind behavior. Intrinsic motivations are considered to be most vital since they are related to internal rewards for setting expected behavior. In other words, a person performs behavior for the behavior itself, and the enjoyment it provides. Extrinsic motivations, in contrast, are regulated by external sources. This implies that the motivation for performing certain behavior is not integrated in a person's beliefs and that he/she would only perform this behavior when rewarded by others. The behavior is considered to be a means to an end, and not for the behavior in itself.

Self-determination has also been applied to sharing information online (Chiu, Wang, Shih, & Fan, 2011; Marett & Joshi, 2009). Contributing to an online discussion in a community to provide others with helpful information for example, would be considered an intrinsic motivation, whereas doing the same in order to establish a reputation among other community members would be considered and extrinsic motivation (Chiu et al., 2011). In our research we applied a similar approach and categorized six potential motivations for sharing physical activities online based on literature review: altruism, information sharing, self-monitoring, goal commitment, social support, and connecting to others. We considered sharing physical activity out of altruistic, self-monitoring and information sharing motives as intrinsic motivations, since they are performed for the internal reward they provide. Goal commitment (Vallerand, 1997), social support seeking, and connecting to others are assumed to be extrinsic motivations (Deci & Ryan, 1975) since they rely on external factors for their fulfilment. In the remaining part of this section, each of the motivations is briefly discussed and applied to sharing physical activity on social networking sites.

Altruistic intentions have been connected to online information sharing in earlier research. Wang & Fesenmaier (2003) demonstrated that people showing altruistic behaviors are more likely to share knowledge in a virtual community. Hsu & Lin (2008) illustrated that altruism along with reputation building had a significant impact on the attitude toward blogging. They defined altruism in blogging as a means of trying to help others with similar issues by blogging about their experiences. Translated to physical activity, we expect that by sharing physical activities on social media, recreational athletes might be attempting to inspire their online peers to start or keep up their exercising. We hypothesize that there is a significant relationship between altruistic motives and physical activity sharing.

Information sharing has taken on a new dimension since the rise of social media and social networking sites like Facebook and Twitter. People increasingly share photos, statuses and location information with an online audience, or basically, they are letting their online peers know what they are up to. Some also start doing this for their physical activities and inform followers about their sports performances. This way, they are showing their online peers that they are actively engaging in healthy behavior and that they are enjoying it. In this research we consider sharing information as having no other intention in mind but to 'let others know what you're up to'. We hypothesize that this desire to share information with online peers is influential to sharing physical activities online.

Research demonstrated the effect of *self-monitoring* on behavior (Aittasalo et al., 2006). Through self-monitoring we can receive feedback on our behavior which possibly leads to adjustments, improvement, follow up on goals, commitment and increased motivation. It is considered a key component in, among others, weight control programs and has shown to be highly effective in increasing physical activity behavior (Aittasalo et al., 2006; M. B. Conroy et al., 2011). The growing use of wearable devices in combination with physical activity has made self-monitoring easier. We hypothesize that sharing with online peers is related to this self-monitoring behavior.

Goal-setting is fundamental to motivation (Meyer, Becker, & Vandenberghe, 2004). It is one of the most prominent strategies in behavioral change. *Commitment to accomplishment* is vital to reaching a goal, along with feedback, ability and task complexity. Sharing physical activities with (online) peers to demonstrate goal commitment might imply a strategy to keep oneself motivated. We therefore hypothesize that sharing physical activities to show commitment to albeit publicly communicated physical activity goals will lead to increased sharing.

Sharing physical activity may trigger reactions of peers which can be motivational in nature. Receiving 'likes' on Facebook or positive comments may work as a stimulant equivalent to 'real-life' social support and could promote physical activity adherence in the individual. In an experiment with pedometers, Foster et al. (2010) found that the daily number of steps significantly increased in the experimental condition in which steps could be shared on Facebook when compared to the other experimental condition in which this was not possible. Similar to Foster et al., other research assessed the influence of social interaction on daily step counts. Consolvo et al. (2006) found that those allowed to share their daily step count online reached their recommended daily number of steps more often when compared to those for whom this was not possible. These participants also indicated that receiving positive reactions and encouragements from others was motivating. Therefore we hypothesize that *seeking online behavior reinforcements* will lead to increased sharing of physical activities.

People also often use social media to *reach out and find people* with a common mindset. Hsu & Lin (2008) assessed community identification, reputation building and expected relationships as motivators for blogging. They consider social identification as an important factor in this regard. Through active blogging, identification with the blog might increase the ‘bonding’ with other bloggers, resulting in a stronger community. Indeed, their results indicate that community building is a strong determinant of the intention to actively blog. It is conceivable that sharing physical activities with online peers might also be related to reaching out to athletic communities on Facebook or Twitter. We therefore hypothesize that people share their physical activities on Twitter and Facebook to find and relate to others with a similar physical activity related interest.

3. Methods

In this section, we provide a detailed overview of the methodology applied in this research and discuss the data collection process (API and survey). In addition, we present a structural equation model developed to measure the impact of the six abovementioned motivations on physical activity sharing via social network sites Facebook and Twitter.

Data collection

Using a custom PHP-script that addressed the Twitter Application Program Interface (API), we collected a sample of 10,000 tweets, originating from a larger database of tweets containing the hashtag #Strava. These tweets are sent by Strava users. Next, these Strava users who shared a physical activity, logged with Strava, with their followers on Twitter, were sent an invitation to participate to our research by means of a comment to the last activity they posted on their Strava profile page. The comment contained a URL that linked the Strava users to the online survey of our research. In total, 400 athletes completed our questionnaire.

Measures

All six determinants of sharing physical activities on Twitter and Facebook were measured using one or two items rated on five-point Likert scales ranging from ‘totally disagree’ (1) to ‘totally agree’ (5). Table 1 provides the items for each of the six determinants with the accompanying mean and Cronbach’s alpha values. Cronbach’s alpha is a measure of internal consistency of constructs and is expected to be at least .70 for exploratory scales for sufficient internal consistency (Hair, Tatham, Anderson, & Black, 2006). All determinants reached the expected value. ‘Connecting’ was measured as a single-item construct, which implies that no Cronbach’s alpha value could be calculated. Sharing physical activities on either Facebook or Twitter was also measured using a five-point Likert scale. The respondents were asked to indicate how often they share the physical activities they log with their online peers on Twitter or Facebook. The scale ranged from ‘never’ (1) to ‘(practically) always’ (5).

Table 1

Construct mean and internal consistency

Construct	Measurement items	Construct mean	Cronbach's alpha
Goal commitment	To hold myself accountable for the goals I've set	3.31	.90
	To commit myself to the goals I've set		
Self-monitoring	To log my training	3.07	.88
	I do it as a way of monitoring my training		
	To follow up on my training		
Social outcomes	Because I like receiving feedback on my workouts	3.77	.81
	Because receiving positive feedback on the workouts that I share, is a good motivation to keep exercising		
Altruism	To help others to start exercising	3.47	.92
	To motivate others to start exercising		
	To keep others motivated		
Information sharing	Informing others on my pastimes	3.73	.70
	Because I like sharing my workouts on social networking sites		
	To let others know what I'm up to		
Connecting	To connect with others who exercise	3.68	-

Model

Based on our hypotheses, we built a model connecting all three intrinsic (altruism, self-monitoring, information sharing) and extrinsic motivations (goal commitment, social support, connecting to others) to sharing physical activity on Twitter and Facebook. The six motivations are considered independent variables, physical activity sharing on either Facebook or Twitter are the dependent variables in the model. The following hypotheses were tested:

- H1a/b: The desire to demonstrate commitment to an athletic goal to online peers will lead to increased sharing of physical activities on Twitter/Facebook;
- H2a/b: The need to keep track of physical activities will lead to increased sharing of physical activities on Twitter/Facebook;
- H3a/b: The desire to receive feedback from online peers on performed physical activities will lead to increased sharing of physical activities on Twitter/Facebook;
- H4a/b: The desire to increase physical activity in online peers will lead to increased sharing of physical activities on Twitter/Facebook;
- H5a/b: The need to share everyday activities with online peers will lead to increased sharing of physical activities on Twitter/Facebook;
- H6a/b: The desire to connect to other with similar physical activity interests will lead to increased sharing of physical activities on Twitter/Facebook;

4. Results

Sample description

Before discussing the results and model fit, we present a brief overview of our survey sample. The majority of the Strava users who responded to our invitation and completely filled out the questionnaire are male (92%), with an average age of 42 years old (SD = 9.22). The majority of the sample are cyclist (92%) while 52% is (also) a runner. Other activities practiced by members of the sample are swimming (8%) and gym/weightlifting (4%). 74% always logs their physical activities with Strava. Every respondent shares his/her activities on social networking sites to some extent. 87% shares on Facebook and 100% shares on Twitter, which is due to recruitment on Twitter.

Model

The model was measured using a structural equation modeling approach. Software package AMOS 21 was used for data analysis. Maximum likelihood estimation was applied. First, the overall fit of the data to our model was assessed using Root Means Square Error of Approximation (RMSEA) and Comparative Fit Index (CFI). RMSEA lower than 0.08 indicates a good model fit. CFI values must be higher than .95 (L. t. Hu & Bentler, 1999). A satisfactory fit for our model was obtained, with RMSEA and CFI scoring .052 and .977 respectively.

Out of the six proposed determinants, all three intrinsic motivations had a significant impact on sharing of physical activities on Facebook and/or Twitter (see Figure 1). Altruism has a significant impact on sharing on Facebook (H4b) but this is also not the case for Twitter (H4a). Sharing physical activities as a part of information sharing with an online peers is the most important motivation and applies to both sharing on Facebook (H5b) and Twitter (H5a). Self-monitoring has a significant impact on sharing on Facebook (H2b) but, as with altruism, not on Twitter (H2a). For the three extrinsic motivations, no significant impact was found. Based on the results, committing to goals (H1a and H1b), seeking confirmation from online peers (H3a and H3b) and connecting to others (H6a and H6b) are no determinants for sharing physical activity on Facebook and/or Twitter. In total, the model explains 20% of the variance in sharing on Facebook and 20% of the variance in sharing on Twitter.

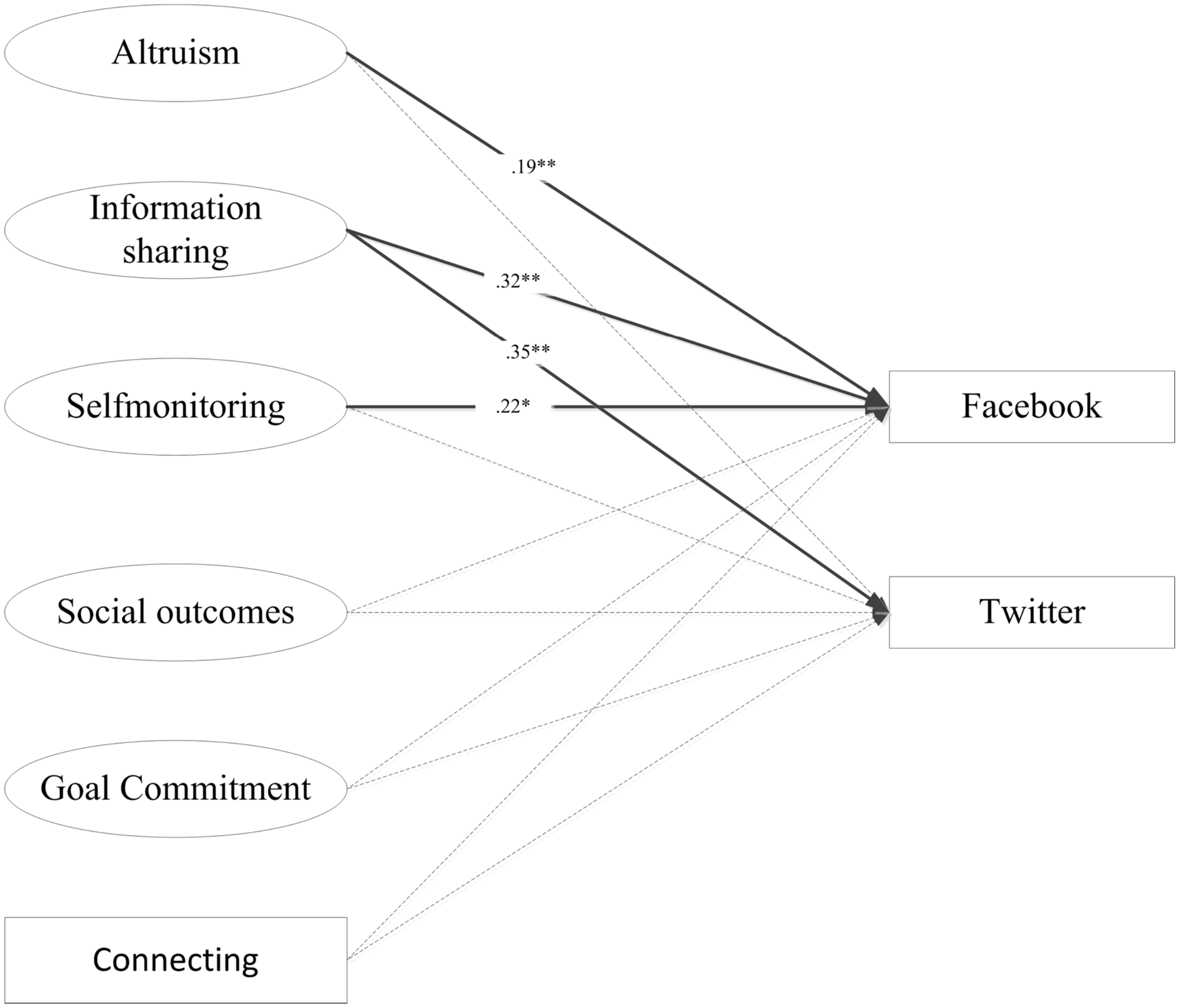

Figure 1: Determinants of physical activity sharing. Significant regression coefficients are shown on the arrows (*=p<0.05;**=p<0.01;***=p<0.001). Dotted arrows are not statistically significant.

5. Discussion and conclusion

This study's objective was to identity motivations for physical activity on online social network sites. A distinction was made between intrinsic and extrinsic motivations. Results suggest that mainly intrinsic motivations are of importance when sharing physical activity. Furthermore, contrary to what was expected, none of the extrinsic motivations appears to have a substantial impact on physical activity sharing behavior via social networking sites. Goal commitment, implying that one wants to invigorate a specific goal by sharing the road towards this goal with an online public does not seem to be a motivator. Of course, this motivation would only be applicable to those recreational athletes working towards a specific goal such as a race or event. Unfortunately our data does not contain any information on whether this is the case for (how many of) the athletes in our sample. Social outcomes, implying that one shares a physical activity on a social networking site to obtain feedback and or support from online peers, was also not identified as a determinant. Based on previous research, however, we expected this to be the case. Also, connecting to other athletes does not seem to be a driver for sharing physical activities on Facebook or Twitter. It may well be that this is more applicable to online communities, as previous research by Wicks et al. (2010) suggests. The results demonstrate that sharing physical activities as part of a more generalized sharing of information with online peers seems to be the most important determinant and applies to both the online audiences on Facebook and Twitter. Altruistic motives, meaning one wants to motivate online peers to start exercising by sharing physical activities as a means of setting an example, applies especially to Facebook and not to Twitter. A higher degree of anonymity on Twitter (Huberman, Romero, & Wu, 2008; Hughes et al., 2012), may partly explain the discrepancy we found in the altruistic motives between both social networking sites with regard to sharing physical activities. Self-monitoring is a motivation of sharing physical activities on Facebook but apparently, this is not applicable to Twitter. Further research should investigate this discrepancy.

To conclude, in this article we have discussed the determinants and motivations of sharing physical activity on social networking sites. Based on a literature review, six potential determinants (altruism, information sharing, self-monitoring, goal commitment, social support and connecting to others), rooted in self-determination theory were selected and applied in a structural equation model in an attempt to explain status updates on Twitter and Facebook.

The results indicate that intrinsic motivations (altruism, information sharing and self-monitoring) have a significant impact on sharing physical activities on Twitter and/or Facebook. Surprisingly, and in contrast to other studies on contributing to social networking sites research, extrinsic motivations (goal commitment, social support and connecting to others) were found to have no significant impact on sharing physical activity. This unexpected result therefore needs further inquiry, but it is likely that the results are influenced by research setup. We therefore suggest a follow-up study that distinguishes between different types of Strava users based on athletic and/or psychosocial variables. It is plausible that depending on how competitive a person is or what his/her goals are, his/her reasons or motivations for sharing physical activities with online peers might vary as well. Distinguishing between athlete types might increase the explanatory value of the model, and provide a deeper insight in the physical activity sharing behavior of recreational athletes.

CHAPTER SIX: EXERCISING MOTIVATIONS, AFFORDANCES AND ONLINE FITNESS COMMUNITY USE

1. Contextualization

Our theoretical framework, presented in Chapter three, illustrates how complementing the self-regulatory affordances of fitness trackers, apps and their data analysis platforms with social affordances could improve their efficacy in keeping people physically active, through better addressing their need for relatedness. In study 3, we subjected this model to an empirical test by assessing how varying motivations for exercising are effectively addressed and supported by the features offered in OFCs. As OFCs give way to varying affordances, we wanted to evaluate how differing motivations for exercising (running in this case) lead to diverging feature use. As such, this study provides an answer to our third research question: *How are motivations for exercising linked to the affordances of OFCs?*

All people to some extent seek fulfillment of their basic need for competence, autonomy and relatedness. In this regard, people have diverging motivations for exercising. Completing a marathon, adopting a healthier lifestyle, losing weight or social contact with others are all examples of goals people want to attain through exercising; and attainment of these goals ultimately leads to basic needs fulfilment to a certain extent. OFCs can accommodate and support motivation for these behaviors through their self-regulatory and social affordances. The question that rises is whether OFC features are indeed used as such? In other words, do people who are driven more than others by social motivations for exercising, for example meeting new people, also use the social OFC features more than others? Or do people who want to attain a specific goal make greater use of self-regulatory features compared to those who are less goal-oriented?

An online survey (N: 717) was conducted among OFC users, recruited via social media, running teams and municipal running initiatives. The data was analyzed using Structural Equation Modeling (SEM) (Kline, 2016). This study contributes to the objective of this dissertation as it brings the full theoretical framework into practice, demonstrating which motivations lie at the basis of OFC use.

Study III: Going the Distance… With a Little Technological Help? Recreational Athletes' Running Motivations as Predictors of Their Use of Online Fitness Community Features

Behavior & Information Technology – *In review*

Jeroen Stragier & Mariek Vanden Abeele

Abstract

Fitness wearables and apps provide users with quantified information about their physical activity patterns. Usually, users access the information on Online Fitness Communities (OFCs) such as RunKeeper or Strava. These OFCs do not only provide feedback on the user's performance, but also offer additional social networking and gamification features. To date, it remains unknown to what extent the different features present in OFCs answer to users' motivations to physically exercise. This study addressed this question, by examining (1) whether there are differences in motivations for running between OFC users and non-users, and (2) whether the use of particular features (e.g., self-regulatory features) is driven by particular running motivations (e.g., weight loss). To that end, a survey study was conducted among 717 runners, of which 57% used an OFC to support running activities. Results show that OFC users are more achievement- and competition-oriented than non-OFC users, and are more in search of recognition for their achievements. As expected, different running motivations predicted the use of different features. These findings are valuable to developers, health practitioners, and individual athletes, as they give insight into how OFCs can be optimally designed and implemented to support users in sustaining their motivation for running.

Keywords:

Online Fitness Communities, self-determination theory, wearables; affordances, running motivations, sports

1. Introduction

Every runner, from beginner to experienced, has his/her reasons for going the distance. Some run, for example, to clear their minds, other to lose weight or become fitter and some train to participate in races (Masters et al., 1993; Slay, Hayaki, Napolitano, & Brownell, 1998). Research shows, however, that while starting an exercise regime can depart with a high level of motivation, many runners fail to keep up their activity, and eventually withdraw (Dishman et al., 1985). A lack of intrinsic motivation, and – particularly for those athletes who are more externally motivated – a lack of external resources such as social support and feedback on behavior are often at the basis of this drop out.

Over the past ten years, however, we have witnessed the development of wearable technology in the form of fitness trackers and fitness apps. These wearables aim to support people in their everyday exercise activities by providing them with detailed, quantified information about their exercise behavior. This information is captured in parameters such as heart rate, step counts, distances covered and minutes of physical activity.

The quantification of behavior results in large amounts of data. To make sense of these data, most commercially available fitness trackers and apps include an online data analysis platform. On these platforms, the fitness tracker owner receives feedback on his/her physical activity via a dashboard that summarizes, analyzes and visualizes the physical activity data. Whereas some of these platforms are brand-based (e.g., Garmin™) and generally only allow the user to upload data from their brand of fitness trackers, other platforms, such as Strava™, RunKeeper™, MyFitnesspal™ or Endomondo™) have emerged that enable their users to upload data from various brands of wearables. These platforms generally offer the same self-regulatory affordances of the brand-based platforms. In addition, they oftentimes provide their users with various social networking features. Because of the latter features, these platforms are usually referred to as 'Online Fitness Communities' or 'OFCs'. Through their self-regulatory and social features, these OFCs are believed to help people to stay motivated to keep up their exercise behavior.

Although the belief is oftentimes expressed that OFCs have untapped potential for supporting people in their physical activity, to date, research into OFC usage is scarce. This is unfortunate. After all, obtaining a nuanced insight into who uses which features and why, may help both developers in the health industry and health practitioners to avoid a 'magic bullet' approach to OFCs/wearables. This study presents a starting point, by exploring if OFCs can support various types of motivations for running through their actionable properties.

Drawing from the results of a survey study among 717 runners, this study aims to address two research questions. First, we identify whether there are differences in motivations for running between OFC users and non-OFC users. By doing so, we want to assess if OFCs attract runners with different motivational backgrounds than those who prefer not to use an OFC. Second, we assess whether the use of certain OFC features is predicted by certain running motivations; for example, if a runner who finds his/her motivation for running in achieving personal goals, makes greater use of the self-regulatory features in OFCs, whereas a runner who runs mostly because of the social recognition that it delivers, may use the social networking features more frequently. If these patterns can indeed be found, this indicates that the OFC user base is heterogeneous in terms of the underlying motivations for feature use. These insights can be used by health practitioners and health technology developers to better understand which features of OFCs aid which groups of users in the support of their physical activity most successfully.

2. Theoretical framework

Running motivations

Some run to clear their minds, other to lose weight and some train to participate in races. Motivations for running are diverse; Hence, it is no surprise that research into motivations for exercising is extensive (Calvo, Cervelló, Jiménez, Iglesias, & Murcia, 2010; Deci & Ryan, 2008; Hagger & Chatzisarantis, 2007; Ingledew & Markland, 2008; Kilpatrick, Hebert, & Bartholomew, 2005) and various instruments have been developed to quantitatively assess athletes' motivations (Li, 1999; Pelletier, Fortier, Vallerand, Tuson, & et al., 1995; Wininger, 2007). Although several theoretical perspectives can be applied to understand exercise motivation, the extant body of research shows that it is most often studied from a Self-determination approach (Deci & Ryan, 2008; Ryan et al., 2008; Silva et al., 2008).

According to Self-Determination Theory or SDT (Deci, 2002; Deci & Ryan, 1975, 2002), every person innately strives for fulfillment of the basic needs of autonomy, competence and relatedness. Autonomy refers to an individual's need to feel be in control of their behavior, while competence refers to the need to feel effective and successful at the behavior one is engaged in. Relatedness, then, refers to our need to perform behavior in a meaningful relation to others, to feel like we 'belong' (Deci & Ryan, 2002).

Over the years, several motivations for exercising have been differentiated on the basis of the SDT framework (González-Cutre & Sicilia, 2012). The Exercise Motivations Inventory (Markland & Hardy, 1993), for example, applies SDT as the basis to distinguish 12 either intrinsic or extrinsic categories of motivations for exercising: stress management, weight management, recreation, social recognition, enjoyment, appearance, personal development, affiliation, ill-health avoidance, competition, fitness and health pressure. For running in particular, the Motivations of Marathoners Scale represents similar work. Although the scale was developed for marathoners, it has been applied to assessing running motivations in various types of runners and distances from 5k up to ultra-run distances (Krouse, Ransdell, Lucas, & Pritchard, 2011; Ogles, Masters, & Richardson, 1995) and adapted for measuring motivations for performing other activities and sports (Buning & Walker, 2016; LaChausse, 2006). The scale distinguishes between four categories of motivations for running, encompassing nine subcategories: physical motives (weight concern, general health orientation, social motives (recognition, affiliation), achievement (competition, personal goals achievement) and psychological motives (life meaning, self-esteem and psychological coping).

Whether an individual runs to get recognition, to get healthy or to enter in a race event, keeping up the motivation to run can be hard. Wearable technology is increasingly receiving attention as a means to support exercise behavior such as running. More specifically, OFCs, online data analysis platforms on which one can upload, analyze and interact with other upon data collected with various types of wearable fitness trackers, can assist runners on various levels.

OFC features and self-regulatory affordances and social affordances

OFCs generally contain a broad range of features which can be aggregated into three feature categories: self-regulatory, social and gamification features. Through these features, OFCs enable a set of motivational 'affordances', more particularly self-regulatory and social affordances.

The concept of affordance is increasingly studied in social sciences, especially in relation to the use of digital media. 'Affordance' refers to the perceived utility of a technology and its technological properties (Norman, 1999; Schrock, 2015). The technological capabilities of a technology provide users with functionalities or features that allow them to interact with the technology in a meaningful way and as such, create value and take advantage of these features.

In this study, we specifically focus on motivational affordances of technology, a concept closely linked to SDT. Motivational affordances of ICT occur when basic needs (autonomy, competence, relatedness) satisfaction is achieved through feature use of an ICT object (Deterding, 2011). OFC features, i.e. self-regulatory, social and gamification features, enable two types of motivational affordances: self-regulatory affordances and social affordances.

Self-regulation is a phased process that requires individuals to exercise influence over their motivations and behavior through self-reflection and self-reaction (Bandura, 1991). Self-monitoring and goal-setting are key subsystems in this regard. Self-regulatory affordances in OFCs, are enabled through self-regulatory features, which constitute a large part of the available features in OFCs. They enable users to self-monitor their exercise behavior, set goals accordingly and monitor their progress through, for example, calendar functions which quickly visualize how often the user has exercised in the last week and specify a goal towards which the user wants to progress. Such features have the potential to help a user satisfy his/her need for competence and autonomy by giving them data-based feedback and offering gamification features such as virtual rewards for goal-attainment (Deterding et al., 2011; Zhang, 2008).

Social affordances of OFCs then, are enabled by letting the user connect and share activities and experiences with online peers and stimulating interactions and conversations with these others. Social features on OFCs are centered around (1) Social affordances related to membership, i.e. creating a personal profile page which can then be consulted by other users, (2) Social affordances for personal expression, i.e. allowing the user to personalize his/her profile, with for example pictures but more particularly with exercise related content (activities) and (3) social affordances of connection, i.e. allowing the users to connect to each other, comment and like each other's activities (Parks, 2011). Additionally, OFC users can share their activities on other social network sites such as Facebook and Twitter and enjoy similar social affordances enabled by those platforms.

Social features have the potential to satisfy an OFC user's need for relatedness and competence, by connecting him/her to (online) peers and affording reception of feedback from others, including motivating messages and endorsement for achieved goals (Stragier & Mechant, 2014; Zhang, 2008). Social gamification features, such as leaderboards can also enhance once sense of competence and relatedness by creating a competitive environment with online peers (Deterding, 2011; Deterding et al., 2011).

Given these particular sets of affordances, it may be that runners who seek out OFCs to support their physical activity differ in terms of their underlying motivations for running from runners who do not rely on an OFC. Hence, the first research question that guides this study is whether there are differences in the motivations for running between OFC users and non-OFC users (*RQ1*).

OFC users: a heterogeneous group?

Depending on their motivations, runners may also use the different types of features present in OFCs to varying degrees. Therefore, the second research question guiding this study is whether there are relationships between different motivations for running (i.e., physical, social, achievement and psychological) and the use of specific OFC features for running (i.e., self-regulatory features, social interaction features on the OFC, sharing activities on social media and gamification features).

When people primarily have physical motivations for running, such as a desire to lose weight or generally become fitter or healthier, they may be more inclined to seek feedback on their behavior and progress. We expect that runners who share these motivations will largely focus on progressing towards their fitness goals. When they use an OFC, it is thus plausible that they will mainly want to see data, information and feedback on their behavior and progress, such as the calories they're burning, the distances they are able to sustain and the paces they can maintain. We therefore hypothesize that:

H1: Physical motivations for running positively predict self-regulatory feature use.

Some people mainly want to exercise with others to make connections and affiliate with other runners. Doing so, they may experience a sense of belonging or relatedness. This social aspect of running is an important determinant of motivation (Sallis, Prochaska, & Taylor, 2000; Utter, Denny, Robinson, Ameratunga, & Watson, 2006). For some, joining a running group or meeting up with others to go running may not always be possible, for example, due to time constraints. This implies that they may be compelled to run individually, deprived of any social interaction. Social features on OFCs may partly fill this gap by allowing runners to keep in touch and endorse each other for their activities online and as such create a 'virtual running team experience'. We therefore assume that:

H2a: Social motivations for running positively predict on-platform social interaction feature use.

H2b: Social motivations for running positively predict off-platform sharing and social interaction feature use.

Some runners are primarily competition-, goal- or achievement-oriented. This is likely to imply that they seek useful information and feedback about the progress they're making. The majority of the features in OFCs is focused on affording this type of self-regulatory feedback to its users, so we expect:

H3a: Achievement motivations for running positively predict self-regulatory feature use.

Furthermore, we expect that these runners will also seek recognition for their achievements among their peers. The use of social features in OFCs affords this type of social feedback. Sharing their activities on social media further increases their reach and chances for social feedback and recognition, which in turn can strengthen their sense of relatedness and competence, as stated in the Cognitive Evaluation Theory (Deci & Ryan, 1985). We therefore expect that:

H3b: Achievement motivations for running positively predict social interaction feature use.

H3c: Achievement motivations for running positively predict off-platform sharing and social interaction feature use.

The competition-orientation of some runners is likely to stir their interest for gamification features. Some features, such as leaderboards, allow the user to compare themselves to other users and enter in competition for the fastest running time on a specific course for example. Also, this competition-orientation will presumably result in a greater interest in gamification features as virtual badges or medals.

H3d: Achievement motivations for running positively predict gamification feature use.

Lastly, some runners primarily have psychological motives for running, for example to increase their self-esteem or to feel better about themselves (Ogles & Masters, 2003). These psychological motives of running can be related to social affordances of running as getting positive feedback on behavior has been shown to increase one's self-efficacy and self-esteem (Anderson, Wojcik, Winett, & Williams, 2006; Williams & French, 2011). We therefore expect that:

H4a: Psychological motivations for running positively predict social interaction feature use.

H4b: Psychological motivations for running positively predict off-platform sharing and social interaction feature use.

Although the potential of gamification in health behavior receives considerable attention, evidence of its effectiveness for changing health behavior is inconsistent (Hamari, Koivisto, & Sarsa, 2014; Lister et al., 2014). Hanus & Fox (2015), for example, suggest that giving external rewards could be deleterious for intrinsic motivation. Furthermore, Dijkstra et al. (2008) indicated that upward social comparison, for example, comparing to those who deliver a better performance at a given task can induce negative feelings towards the self and lead to negative self-image. Leaderboards in OFCs are to a large extent generic and do not afford adaptive social comparisons. We therefore hypothesize that:

H4c: Psychological motivations for running negatively predict gamification feature use.

Figure 1 depicts the theoretical model for this study.

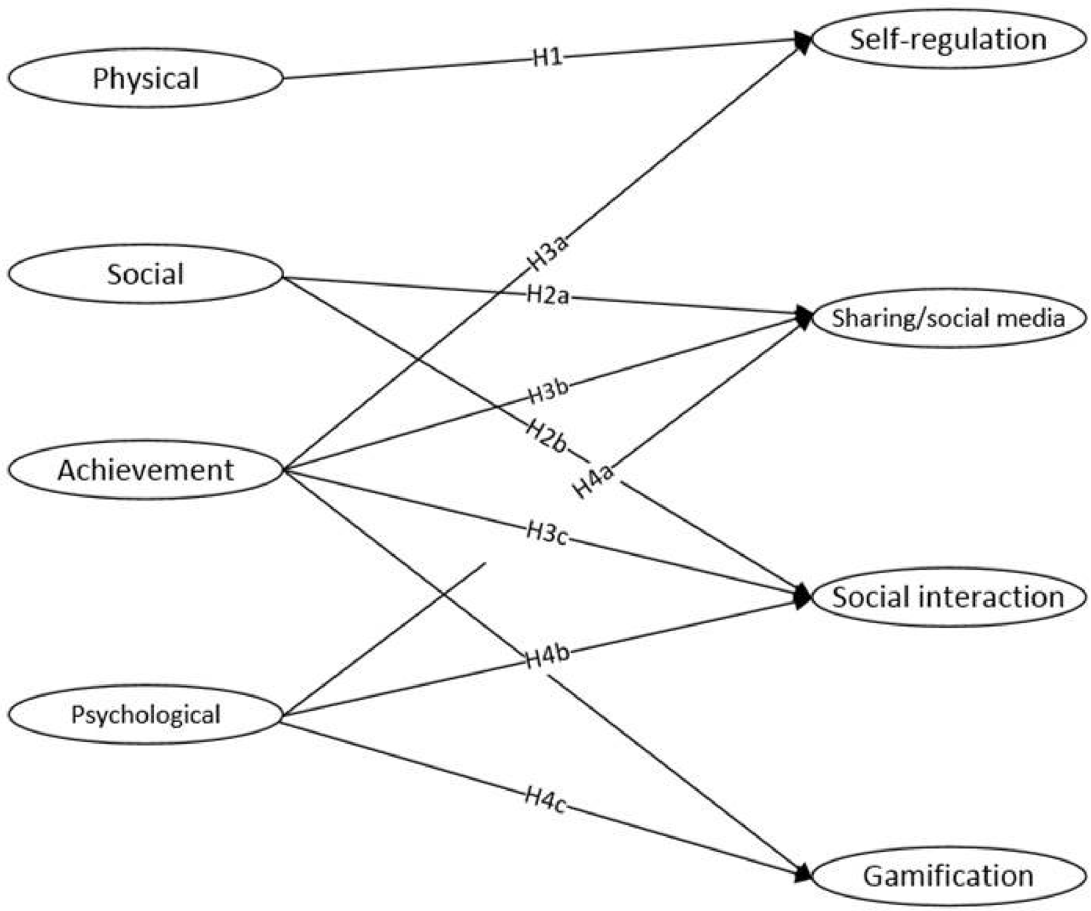

Figure 1 Theoretical model

3. Methods

Data collection procedure and sample description

From March to June 2016 an online survey was distributed under the running community through various social media channels (e.g., Facebook & Twitter), local running groups and communal 'start-to-run' initiatives. Runners of at least 16 years of age were eligible for participation in the study. No criteria for running habits were imposed. This recruitment procedure resulted in a final sample of 717 runners, of which 56% were females. The average age in the sample was 38 years (*SD*=11.29). The male runners in the sample were 40 years

(*SD*=11.56) on average, the female runners were on average 37 years old (*SD*=10.94), $t(715)=3.30$; $p=.001$. The majority of the sample (61%) had been running for more than two years, 22% started running no later than 6 month prior to taking the survey. The majority of the sample (70%) runs two to three times per week. More than half of the runners (57%) in the sample declared to be a member of an OFC for running. Men appear to use them more often (62%) than women (53%), ($\chi^2(1)=0.11$, $p=.007$). RunKeeper (27%) and Strava (17%) were the most commonly used OFCs among the runners in our study.

Measures

Running motivations. To measure motivations for running, the Motivations of Marathoners Scale or *MOMS* (Masters et al., 1993; Ogles & Masters, 2003) was used and translated to Dutch. A reduced version was used, using 34 of the original 56 items. This was done to reduce overall length of the questionnaire and as such reducing the effort for the respondent (in order to lessen fatigue and ensure proper completion of the survey). Exploratory factor analysis supported the same clustering of items into motivations as in the initial *MOMS*-questionnaire. Table 1 lists the items used, together with their beta-weights in the final structural equation model (see below). The means, standard deviations and Cronbach alpha-values can be found in Table 4.

Table 1

Running motivation items (taken from the Motivations Of Marathoners Scale (Masters et al., 1993; Ogles & Masters, 2003))

			β
Physical motives			
	Weight control		0.65
		To keep my weight under control	0.91
		To lose weight	0.94
		To look leaner	0.89
	General health orientation		0.84
		To improve my health	0.82
		To become more fit	0.87
		To stay in physical condition	0.70
		To prevent illness	0.50
Social motives			
	Affiliation		0.71
		To meet people	0.88
		To socialize with other runners	0.91
		To share a group identity with other runners	0.80
		To participate with my family or friends	0.59
	Recognition		0.85
		To earn respect of peers	0.86
		To make my family or friends proud of me	0.81
		To make people look up to me	0.90
		To get compliments from others	0.84
Achievement motives			
	Competition		0.97
		To compete with others	0.83

		To see how high I can place in races	0.69
		To get a faster time than my friends	0.79
		To beat someone I've never beaten before	0.77
	Personal goal achievement		
		To compete with myself	0.69
		To push myself beyond my current limits	0.58
		To see if I can beat a certain time	0.60
		To see if I can run a certain distance	0.48
Psychological motives			
	Psychological coping		0.92
		To feel less anxious	0.55
		To distract myself from daily worries	0.54
		To improve my mood	0.66
		To concentrate on my thoughts	0.70
	Life meaning		0.91
		To add a sense of meaning to life	0.87
		To make my life more purposeful	0.87
		To make myself feel whole	0.80
	Self-esteem		0.93
		To improve my self-esteem	0.86
		To feel proud of myself	0.70
		To feel a sense of achievement	0.64
		To feel more confident about myself	0.87

*All beta’s (β) are significant at $p<.001$

OFC features. To construct the measure of OFC feature use, we first compiled a longlist of features available in Strava, RunKeeper, Endomondo and Runtastic. The features were categorized into 3 categories: self-regulatory features, social features and gamification features. We retained those features that are common across the different platforms. Social features were further divided into on-platform social interaction features and off-platform sharing and social interaction features. The items asked about the frequency of feature use, measured on a 7-point Likert scale ranging from 'never' to '(almost) every time'. Because the respondents may use different platforms to support their running, we asked them to first indicate the OFC they used most frequently. All subsequent items were user-tailored. An exploratory factor analysis was performed on the items, which revealed a four factor solution, clustering self-regulatory, offline-social, online-social and gamification features.

First, self-regulatory features (5 items; *α*=.68; *M*=5.94; *SD*=.96) allow OFC users to self-monitor their behavior and their track progress. Examples of items regarding the use of such features include '(I use [platform] to keep track of how often I run' and 'I use [platform] to keep track of the running progress I am making'. Second, on-platform social interaction features comprises (8 items; *α*=.96; *M*=2.52; *SD*=1.62) such items as 'Giving a comment to a friend's activity' or 'Making contact with other runners I know'. These features relate to the social affordances of OFCs that enable users to make contact and interact with other users about their running behavior. Off-platform sharing and social interaction features (4 items; *α*=.91; *M*=3.01; *SD*=1.59) provide similar social affordances to OFC users albeit outside of the OFC. OFCs generally give their users the possibility to share their activities with their online peers on social networking sites as Facebook and Twitter and therefore make use of the social networking affordances available on these platforms. Therefore, this feature category contains such features as 'sharing my activity on Facebook' and 'liking a friends running activity on Facebook. Lastly, gamification (2 items; *α*=.68; *M*=2.16; *SD*=1.39) entails those features that bring game elements commonly seen in computer games to the OFC, applied to running. We included two features: 'comparing my activities to those of my friends' and 'checking which trophies/ badges I've earned'.

Table 2 provides the four feature categories with their manifest indicators used in this study, and the beta-weights of the items in the final structural equation model.

Table 2

Items measuring OFC feature use (self-constructed). Platform names were automatically tailored to the OFC that respondents reported using the most.

Category		β
Self-regulatory features		
	Checking my average running speed	0.65
	Checking how long I've been running	0.62
	Keeping track of how often I run	0.37
	Monitoring the progress I make at running	0.41
	Checking how far I've been running	0.57
Off-platform sharing and social interaction features		
	Congratulating a friend who shared a run for his achievement	0.95
	Giving a comment to a run shared by a friend	0.91
	Liking' a run shared by a friend	0.92
	Sharing my runs on social media (Facebook, Twitter…)	0.59
On-platform social interaction features		
	Checking the activities of my Strava friends	0.84
	Giving a comment to a run of a RunKeeper friend	0.90
	Checking if I received comments on my runs	0.93
	Making contact to other runners whom I know	0.84
	Congratulating a Strava friend for completing an activity	0.93
	Liking a RunKeeper friend's activity	0.94
	Checking if I received likes on my runs	0.90
	Adding other runners to my friends list	0.84
Gamification features		
	Comparing my runs to those of other Strava users	0.90
	Checking which badges I've earned with my run	0.60

*All beta's (β) are significant at p<.001

Analyses

To measure differences in running motivations, an independent t-test was performed between OFC users and non-OFC users. To assess if varying motivations for running result in differing use intensities of OFC features categories, a Structural Equation Model (SEM), mapping the relationships between running motivations and OFC feature use was tested.

4. Results

Motivations for running between OFC users and non-users

Nine motivations for running were measured using the MOMS scale: weight concern, general health orientation, recognition, affiliation, competition, personal goals achievement, life meaning, self-esteem and psychological coping. General health concern was the prime motivation for Flemish runners to go running (M=6.14, SD=1.37), followed by attempting to achieve personal goals (M=5.03, SD=1.25). Entering in competition (M=2.83, SD=1.46) or running for recognition (M=2.64, SD=1.40) appeared the least important motivations (see Table 3 for the full list).

The first objective of this article was to assess if motivations for running are different between OFC users and non-OFC users. In order to answer this question, an independent samples T-test was conducted. A significant difference between the two groups was found for achieving personal goals, entering in competition and seeking recognition. Table 3 shows that OFC users are significantly more oriented towards achieving certain running goals (M=5.3, SD=1.11) than non-OFC users (M=4.7, SD=1.35), $t(594)$=6.328; p=0.000. Furthermore, they also participate more frequently in running competitions ($M_{OFC\ users}$=2.97, SD=1.46; $M_{non\text{-}OFC\ users}$=2.65, SD=1.46; $t(715)$=2.97; p=.003) and are somewhat more seeking recognition from their peers ($M_{OFC\ users}$=2.75, SD=1.47; $M_{non\text{-}OFC\ users}$=2.49, SD=1.40; $t(702)$=2.50; p=.013). No significant differences between the groups were found for the other motivations. The results of this analysis already indicate that there is a substantial difference in motivations between OFC-users and non-OFC users. Especially the achievement and competition-orientation of OFC-users is prominent.

Table 3

Means and standard deviations for running motivations of OFC users, non-users and the total sample

	OFC users (n=406)	Non-OFC users (n=311)	Sample (n=717)
Health	6.19 (*SD*=0.90)	6.07 (*SD*=0.92)	6.14 (*SD*=0.91)
Weight	4.68 (*SD*=1.52)	4.58 (*SD*=1.38)	4.64 (*SD*=1.46)
Affiliation	2.89 (*SD*=1.39)	2.99 (*SD*=1.35)	2.93 (*SD*=1.37)
Recognition**	**2.75 (*SD*=1.47)**	**2.49 (*SD*=1.29)**	2.64 (*SD*=1.40)
Competition**	**2.97 (*SD*=1.46)**	**2.65 (*SD*=1.46)**	2.83 (*SD*=1.46)
Personal goals***	**5.3 (*SD*=1.11)**	**4.7 (*SD*=1.35)**	5.04 (*SD*=1.25)
Psychological coping	4.15 (*SD*=1.24)	4.03 (*SD*=1.21)	4.1 (*SD*=1.23)
Life meaning	4.07 (*SD*=1.66)	3.89 (*SD*=1.62)	3.99 (*SD*=1.65)
Self-esteem	4.76 (*SD*=1.4)	4.58 (*SD*=1.35)	4.68 (*SD*=1.38)

*=p<0.05;**=p<0.01;***=p<0.001

Running motivations and OFC affordances

Descriptive analysis. The second objective was to assess if varying motivations for running result in differing use intensities of OFC features categories. Therefore, all non-OFC users (n=311) were excluded from the analysis. Moreover, all OFC users reporting to use any other OFC than those listed in the survey (n=46) were excluded as well, since no information on feature use was available for those users. This left a sample of 360 OFC users for estimation of the model. We further aggregated the 9 motivations for running into four categories: physical, social, achievement and psychological motives.

Table 4 provides the mean values, standard deviations, Cronbach's alpha and zero-order correlations for all constructs in the model. The table demonstrates that self-regulatory features are the category most widely used by all OFC users (*M*=5.94, *SD*=0.96). Sharing features, social interaction features and gamification features are used to a lesser extent, although standard deviations report a fairly wide distribution among OFC users.

Table 4

Descriptive statistics, internal reliabilities and correlations

	Mean	*S.E.*	*Alpha*	1	2	3	4	5	6	7	8
1. Self-regulatory features	5.94	0.96	0.68	1							
2. off-platform sharing and social interaction features	3.01	1.59	0.91	.149**	1						
3. On-platform social interaction features	2.52	1.62	0.96	.116*	.415**	1					
4. Gamification features	2.16	1.39	0.68	.196**	.268**	.705**	1				
5. Physical motives	5.06	1.17	0.84	.108*	.134*	-.126*	-0.04	1			
6. Social motives	2.82	1.24	0.88	0.09	.334**	.245**	.252**	.219**	1		
7. Achievement motives	3.97	1.18	0.84	.255**	.161**	.268**	.324**	-.116*	.544**	1	
8. Psychological coping	4.38	1.26	0.93	.161**	.239**	.114*	.128*	.351**	.449**	.425**	1

*=p<0.05;**=p<0.01;***=p<0.001

Model Fit

A structural equation model of the theoretical model was estimated using SPSS AMOS 21. Bootstrapping was used to handle non-normality of the data (Preacher & Hayes, 2004). The measurement model connects the running motivations measured through the MOMS scale with the four OFC feature categories (self-regulatory features, social interaction features, sharing on social media and gamification features).

A first empirical test of the model showed 4 non-significant paths: from psychological motivations to on-platform interaction features (H4a), off-platform sharing (H4b) and gamification (H4c) and from social motivations to on-platform social interaction features (H2a). These paths were trimmed from the model. This yielded a final model with an acceptable model fit ($\chi^2(1298)=2843.20$, $p<0.001$; $\chi^2/df=2.19$; CFI=0.89, RMSEA=0.058). The final model is shown in Figure 2.

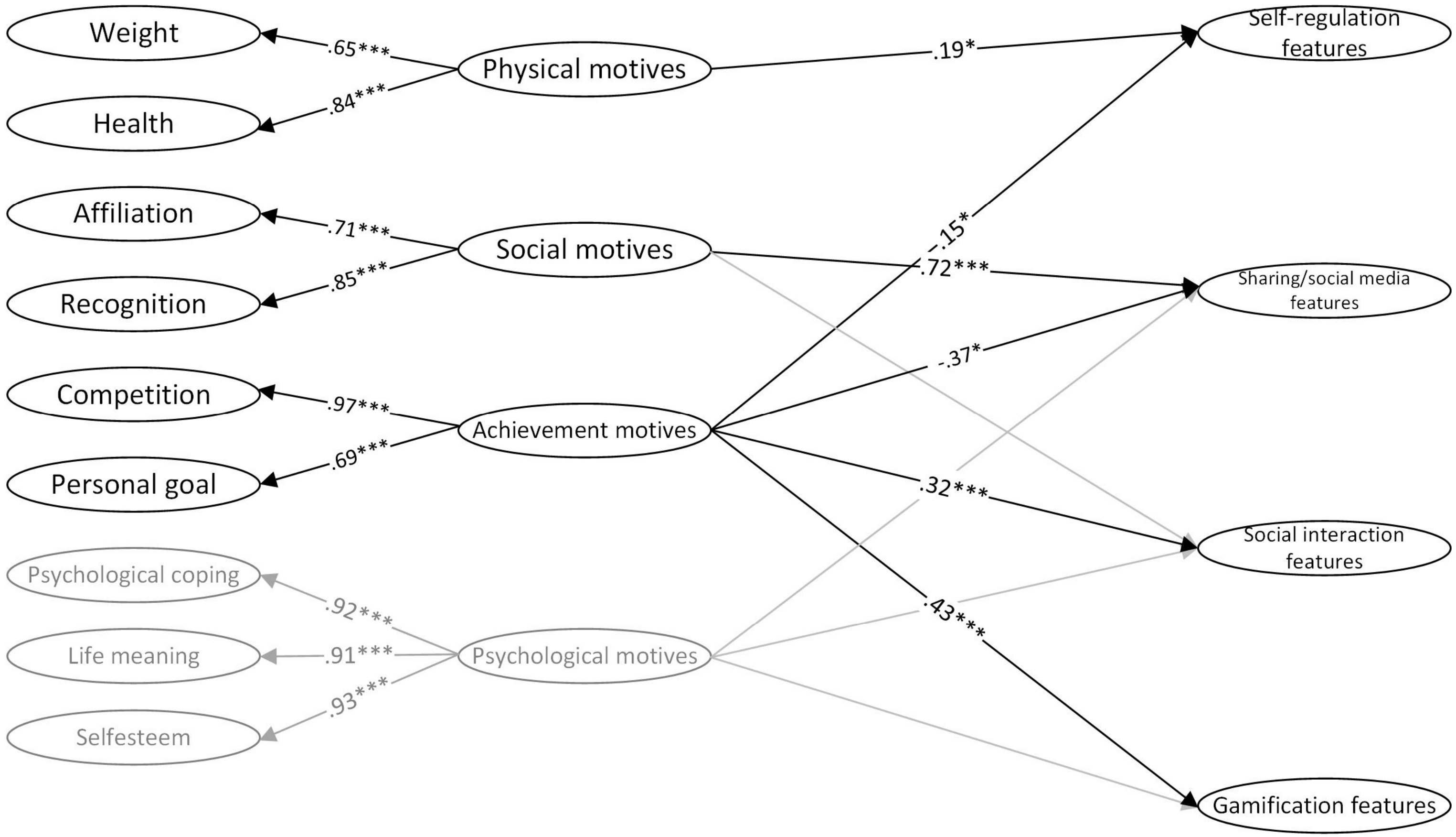

Figure 2 Final structural equation model (*=p<0.05;**=p<0.01;***=p<0.001)

Results indicate that physical motivations (e.g., weight loss) for running were associated with more frequent use of self-regulatory features (β= 0.19, t(1298)= 2.48, p = .013; *H1 confirmed*). Social motivations for running positively predicted sharing activities on other social media platforms (β= 0.72, t(1298)=4.19, p = .000; *H2b confirmed*). The association of social motivations with the use of social interaction features in the OFC itself however, was not significant (*H2a not confirmed*). Achievement motivations positively predicted the use of self-regulatory features (β= 0.15, t(1298)=2.11, p = .035; *H3a confirmed*), social interaction features in the OFC (β= 0.32, t(1298)=5.35, p = .000; *H3b confirmed*) and gamification features (β= 0.43, t(1298)=6.69, p = .000; *H3d confirmed*). On the other hand, they were negatively associated with sharing activities on other social media platforms (β= -0.37, t(1298)=-2.30, p = .022; *H3c not confirmed*). Contrary to what we expected, no significant associations were found between psychological motivations for running and the use of social interaction features in the OFC (*H4a not confirmed*), sharing activities on other social media platforms (*H4b not confirmed*) and gamification feature use (*H4c not confirmed*).

5. Discussion and conclusion

This study focused on (the social and self-regulatory features of) OFCs and how their use can be predicted by motivations for leisure time running. The two objectives of this study were to (1) identify motivational differences for running between OFC users & non-OFC users and (2) to assess whether OFC features are used in accordance with particular running motivations.

The results of our study demonstrate that while for most runners general health orientation, weight concern, enhancing self-esteem and achieving a self-set goal are the main motivation for running, OFC users appear more achievement and competition oriented than non-OFC users. Furthermore, OFC users appear to be more in search of recognition for their achievements.

Analysis of OFC feature use reveals that OFCs are primarily used for their self-regulatory affordances and that social and gamification features are less frequently used. This is mainly the case for those with physical motivations for running, such as losing weight or becoming fitter. Major differences regarding the use of social and gamification features between the respondents are observed however.

It appears from our study that achievement oriented runners find many features that support their motivation: self-regulatory features provide them with informational feedback on their behavior, social interaction features allow them to connect to other runners and get social feedback on their achievement, and gamification features appeal to them from their competitive side. Sharing their activities on social media however, does not appear to be a functionality they appreciate. This finding ran counter to what we expected based on their apparent search for recognition. It is likely that sharing activities is a practice more common among purely recreational athletes and involves mostly casual 'now and then' sharing, i.e. not for every run. Achievement oriented runners interact more frequently within the OFC with fellow 'like-minded' runners, perhaps because they identify more strongly with the identity of a professional runner (rather than an amateur).

Contrary to what we expected, social motivations did not predict social interaction feature use on the platform. We did find a positive association with sharing activities on external social media. It is plausible that on-platform social interaction is currently used for achievement related conversations and therefore does not appeal to recreational athletes with no competition or achievement goals. Sharing on platforms such as Facebook, with peers from their offline network, may therefore be more attractive to the latter. Further research is needed to investigate this matter. After all, the observation that runners with a social motivation mainly use features for sharing activities on external social network sites suggests that different types of athletes turn to specific audiences for social feedback. Competitive athletes look at each other for feedback and comparison, while recreational athlete appear more likely to turn to their direct environment and not to other runners per se, at least not in an online environment.

Runners with primarily physical motivations for running were found to make greater use of self-regulatory features. Feedback on behavior through self-monitoring is a key element of self-regulation, especially in the short term. However, research (Clawson et al., 2015; Lazar et al., 2015) has demonstrated that wearables can lose their motivational affordances in the long term and that therefore, people abandon them rather quickly, once they have obtained a view on what their behavior looks like 'in numbers'. Unfortunately, this often implies that relapse into former (passive) lifestyle habits occurs. Social affordances then, may be a means to keep users more engaged in the longer term (Stragier, Vanden Abeele, Mechant, & De Marez, 2016).

Lastly, no associations between psychological motivations and OFC affordances were found. An explanation for this may be that psychological motives such as 'clearing my mind' can be considered as outcomes more than motives. The positive effects of exercising on psychosocial health are well documented, such as improved self-esteem and more social interaction (DiLorenzo et al., 1999; Eime, Young, Harvey, Charity, & Payne, 2013). OFCs may therefore facilitate psychological outcomes indirectly, rather than directly through the use of its features.

Some implications of this study can be noted. OFCs appear to attract mainly achievement oriented runners, whom see their needs addressed in current OFC features. This indicates that when designing or implementing OFCs, fitness apps or interventions, there may be a niche for less achievement oriented platforms that accommodate the needs of purely recreational athletes, with, for example, a stronger focus on social affordances, or gamification features with less focus on competition. This may make these platforms more appealing to a broader public and more applicable to less competition-oriented activities, such as nutrition and moderately intensive physical activities such as recreational walking. Furthermore, the sharing of activities outside of the OFC indicates that opportunities exist for enhancing the delivery of online social support for physical activity. Lastly, a segmented approach, where elements such as application interfaces can be tailored to user motivations, may be preferable than the generic profiles that are now available on most OFCs. This may, for example, imply that gamification features focused on competition between OFC member could be 'turned off' if these are not of interest to the user.

This study presented a first attempt to connect motivations for exercising to affordances of Online Fitness Communities and by extension, wearable fitness trackers and fitness applications. Further research should extend to other activities besides running and other context in which information technology can successfully support motivation for behavior (change) for example as nutrition and (residential) energy use.

CHAPTER SEVEN: PERSISTED USE OF ONLINE FITNESS COMMUNITIES

1. Contextualization

While study 3 focused on bringing the theoretical model of this dissertation into practice by demonstrating how OFC affordances meet motivational aspirations for exercising, study 4, *Understanding persistence in the use of Online Fitness Communities: Comparing novice and experienced users,* assesses how these affordances contribute to sustained OFC use. It is one of the basic assumptions of this dissertation that adding social affordances to self-regulatory affordances in (online) data analysis platforms can result in sustained platform use and as such, sustained exercise behavior. These social affordances give the user a connected experience, which can make the use of the platform more enjoyable and engaging.

The role of social affordances in OFCs should be approached in a process-oriented way. Using technology to motivate people to become, and even more importantly, stay physically active implies the formation of a habit. Behavioral changes/choices such as taking the stairs at work instead of the elevator, taking the bike to work instead of the car, or going for a run three times per week imply habitual behavioral changes. Technology can be very effective in assisting in the creation of new habits. The key to making behavior habitual is repeating a certain behavior in a specific context until it becomes automatic (Gardner, Lally, & Wardle, 2012). This appears more feasible for smaller behavioral changes (for example consistently taking the stairs instead of the elevator) than broader activity goals such as taking 10.000 steps per day or maintaining an exercise regimen, which is less connected to a specific situation or context.

We explained that the self-regulatory affordances are the prime reason for adopting fitness trackers, fitness apps and OFCs. They can provide us with useful feedback, assist in goal-setting, give us reminders to perform the desired behavior, e.g. going out for a run. Recent research on abandonment of fitness trackers and apps however, indicates that this may not be sufficient. Technology designed for motivating people to become more physically active should deliver a more engaging experience to avoid dropout. Therefore, the assumption that is made in this study is that designing an engaging platform by relying on social interaction, will lead to sustained platform use and as such, indirectly implies sustained exercise behavior. We use the OFC Strava in this study to illustrate that leveraging on a person's online social environment can lead to increased engagement and prolonged platform use. For this study, an online survey was held among Strava users with the objective of testing a SEM model relating OFC affordances to habitual OFC use. The Twitter API was used to collect a database of Strava users and consequently, the Strava API was used to recruit survey participants by means of giving a comment to their most recent activity, posted on Strava. This study contributes to the objective of this thesis as it demonstrates which elements appear to be efficacious at retaining users in the OFC and therefore, indirectly contribute to sustained exercise behavior.

Study IV: Understanding Persisted Online Fitness Community Use: Comparing Novice and Experienced Users

Computers in Human Behavior - *Published*

Jeroen Stragier, Mariek Vanden Abeele, Peter Mechant & Lieven De Marez

Abstract

Mobile and wearable technologies facilitate physiological data collection for health and wellness purposes. Users typically access these data via Online Fitness Community (OFC) platforms (e.g., Fitbit, Strava, and RunKeeper). These platforms present users with functionalities centered on self-monitoring, social networking and enjoyment. In order to fully benefit from these functionalities, users need to make a habit out of integrating OFC use into their everyday workout routines. However, research suggests that few athletes succeed in persisting OFC use over a longer period of time. This study sheds light on the factors that explain persisted OFC use. To that end, the study compares novice and experienced users in terms of their OFC use motives and how these motives contribute to the habitual integration of OFCs into everyday workout routines. Based on the survey responses of 394 OFC users, a multi-sample structural equation model indicates that self-regulation and social motives directly predict habitual OFC use, and that enjoyment and self-regulatory motives indirectly predict habitual OFC use, by driving the perceived usefulness of OFCs. Moderation analysis revealed that, for novice users, self-regulatory motives are the prime drivers of habitual OFC use, while social motives and enjoyment are more important for experienced users.

Keywords

Online Fitness Communities, habit formation, exercise behavior, structural equation modeling

1. Introduction

Technology is increasingly important in the support of regular health and activity monitoring (Kay et al., 2011). Activity tracking applications (apps) and wearables linked to (online) data analysis platforms are considered radically new and self-empowering health technologies that enable their users to track, analyze and interpret health related parameters including step counts, calorie intake, heart rate, exercise frequency and more. These technologies and applications can collect large amounts of activity and health related data.

Because the practice of collecting health related data about oneself is a self-monitoring process that relies on the quantification of one's bodily processes (e.g., heart rate) and activities (e.g., step counts), this practice is also known as the 'Quantified Self' (Barrett et al., 2013; Swan, 2012a, 2012b, 2013). Wearables and apps have boosted the Quantified Self since they afford automated and detailed data collection, resulting in better data quality. In addition, these technologies do not just capture and archive data for the benefit of the 'life-logger' him- or herself, but also afford the user to share his records with others in dedicated online communities or on social network sites.

Fitness apps, wearables and Online Fitness Communities (OFCs) are increasingly attracting academic attention. The focus of academic research is relatively broad, however, ranging from descriptive analyses to intervention studies (Middelweerd, Mollee, van der Wal, Brug, & Te Velde, 2014). Descriptive analyses often focus on identifying the presence of specific elements in fitness apps. West et al. (2012), for example, categorized the types of behaviors addressed in fitness apps. Nutrition, physical activity and personal health and wellness appeared most common. Conroy et al. (2014) examined the prevalence of behavior change techniques in fitness apps. They concluded that fitness apps mostly contained fewer than four behavior change techniques of which self-regulatory features (feedback, planning and goal-setting) and social support were most prevailing. In addition, Lister et al. (2014) found widespread use of gamification elements in fitness apps, although these appear to be seldom framed within behavior change theory. In short, descriptive analyses show that physical activity is a typical activity monitored by fitness apps and that users typically gain access to their data via an online platform that has self-regulatory, social networking and gamification features.

Intervention studies form a second strand of research. These studies examine the potential of e&mHealth devices and applications for behavior change. A number of these studies discuss the potential of OFCs and social media for behavior change in the fields of health and fitness behavior. Cavallo et al. (2012), for example, concluded from their research that integrating Facebook in an intervention may enhance social support for physical activity. Foster et al. (2010) found that using a Facebook application to create a social and competitive context was successful in raising step counts. In short, these studies illustrate that integrating social media in interventions can result in positive health behavior adherence outcomes.

A central conclusion of several intervention studies is that the success of e&mHealth in support of people's health behavior strongly depends on the extent to which users integrate their use in their everyday routines. Intervention studies in the context of physical activity, for example, report significant attrition numbers (Bessell et al., 2002; Malik, Blake, & Suggs, 2014). A commercial study by Endeavor Partners (2014), reports that 50% of new users of wearables and 74% of new users of health apps, stop using them within two weeks. This suggests that only a minority of users succeed in making a habit out of using their wearable or app.

Given the problem of persistence in the use of wearables and apps, it is important to identify potential use motives that contribute to habitual wearable/app use. Greater awareness of these motives informs developers about how products can be improved, provides focus for health practitioners who wish to build successful health interventions and programs that rely on these technologies, and helps both scientists and individual users to better understand the role of these technologies in supporting healthy behavior. It is crucial in this regard to not focus on the devices (i.e. apps and wearables) that capture the data, but rather on the opportunities for feedback they make available, as it is this feedback which has been identified as an important factor for behavior change (DiClemente, Marinilli, Singh, & Bellino, 2001; Free et al., 2013). For most apps and devices, these opportunities for feedback are presented in the form of an OFC.

Online Fitness Communities

Online Fitness Communities (OFCs) are platforms that translate data gathered by a wearable device or mobile app into feedback, both of informational and social nature. OFCs thus generate meaningful information about the user's performance and/or health. Popular examples of OFC's are Strava, RunKeeper, Fitbit and Endomondo. OFCs enable users to either manually add activities to their profile or to upload sessions logged through wearable devices or dedicated smartphone applications which use the available sensors and GPS of the smartphone to automatically log a users' activities once a session is started by the user. After completion of the activity, data is transferred to the user profile using 3/4G or Wi-Fi connection, where users can analyze their performance. OFCs also connect both recreational and professional athletes. Users can view other athletes' activities and can allow others to view theirs. Furthermore, users can interact with others based on the activities they share. On Strava, for example, they can give 'Kudos', which is the Strava equivalent of a 'Facebook like', to activities posted by a Strava user as a means of endorsing each other for achievements. They can also comment on the activity. Users can typically join OFCs with either a free account or a paid premium account, which allows them to use more features of the platform.

In this study, we particularly focus on Strava, an OFC that is experiencing significant growth in recent years, especially among cyclists and runners. Launched in 2011, Strava now has over 10 million users ("A VC Lets a Bet Ride: the Story of Strava," 2013) generating 2 million activities per week ("A Global Data Set," 2014).

OFC affordances and use motives

Although U&G theory has been applauded for focusing on what people do with media rather than on what media do to people, scholars have also critiqued the theory for overly focusing on the social and psychological origins of needs, while dismissing the role that media themselves play in need. The perceived usefulness concept has a pronounced importance in research on technology adoption and use (Bhattacherjee & Premkumar, 2004). For OFCs, this usefulness implies that the OFC must add value to his/her current exercise behavior. Technology developers attempt to generate this added value in the form of technological features that developers believe will assist the user in achieving his/her goals. For instance, as mentioned above, descriptive research has revealed that the most popular OFCs have a number of features in common, such as features to log activities, to interact with others and to set goals (and obtain rewards for achievement).

According to media affordances theory (Hutchby, 2001; Schrock, 2015; Woodruff & Aoki, 2003), technological features can be understood as intrinsic properties of the technology that engender possibilities for action (cf. Orlikowski's (1992) duality of technology). Technological affordances arise when the user perceives these 'actionable properties' (Jensen, 2010). In the context of OFCs, for example, self-monitoring can be considered a technological affordance that arises when users perceive the possibilities that OFCs offer to log metrics on physical activity (e.g., duration, average speed …).

The affordances concept has recently been successfully integrated into motivational theories of media use (e.g., Sundar & Limperos' (2013) renewed Uses & Gratifications theory). Adding the affordances concept to such theories is relevant, because the concept acknowledges that not only psychological and social needs, but also (novel) expectations about the outcomes of technology use - that arise when people perceive the technology's actionable properties - motivate technology use. Because affordances are relational (Hutchby, 2001), however, users may differ in the extent to which they perceive these affordances. This, in turn, may impact how useful users perceive a technology to be.

In the current study, we integrate the affordances concept with Self-Determination Theory (SDT) (Deci & Ryan, 1975, 1985, 2010). SDT departs from the basic premise that three basic psychological needs drive human behavior: autonomy, relatedness and competence needs. Autonomy refers to the need to be in control of one's life. Relatedness comprises a person's need to have meaningful relationships with significant others. Lastly, competence is a person's need to feel effective or successful in his/her undertakings (Deci & Ryan, 2008; Deci & Ryan, 2010). As we will argue below, the actionable properties of OFCs afford gratification of these needs in the context of physical activity and exercise behavior.

Self-regulatory use motives. Self-regulation refers to the process of regulating one's own behavior through processes of self-monitoring, planning, scheduling and goal-setting (Bandura, 1991; Michie et al., 2011). Self-regulation also includes setting self-determined goals or standards in order to become more efficient at reaching targeted behavior. When these goals or standards are reached, this will lead to self-rewarding reactions that can induce further adjustment of goals and continuance of behavior (Bandura, 1977). Self-regulation is closely associated with the fulfillment of autonomy and competence needs (Ryan & Deci, 2000b).

Most OFCs are centered on features that facilitate self-regulatory behavior, as they aim to inform and assist their users while they attempt to reach their goals. In the case of Strava, for example, users have the opportunity to closely self-monitor their exercise data and view their progress over a certain time period in detailed graphs. Users can also set goals to test their competence, such as completing a 5 kilometer running event within a given time frame (e.g. within 6 weeks). The self-monitoring and self-regulatory features of OFCs thus offer ample opportunity for autonomy and competence need satisfaction.

As indicated above, we expect user perceptions of the actionable properties of a technology to drive perceptions of the usefulness of the technology. Users may differ, however, in the extent to which they perceive, value and consequently act upon the self-regulatory affordances of OFCs. We expect that users who are motivated more strongly to use an OFC for the self-regulation affordances that it offers, i.e., users who have stronger self-regulatory use motives, will also perceive OFCs as a more useful support to their work out experience. We thus expect that:

H1: Users' self-regulatory motives for using an OFC positively predict perceived usefulness of the OFC.

Social use motives. Social interaction among people in social networks results in the formation of social capital, a concept capturing many sociological concepts (N. Lin, Cook, & Burt, 2001) including social integration, social cohesion and social support. Research has demonstrated that social support is an important determinant of physical activity adherence (F. Almeida, 2008; Beets et al., 2010; Cavallo et al., 2014; Springer, Kelder, & Hoelscher, 2006) and social support is associated with the fulfillment of people's relatedness needs (Edmondson, 2003; Hale, Hannum, & Espelage, 2005). OFCs offer athletes the opportunity to connect and interact with each other. In the case of the Strava OFC, for example, users can follow others and be followed back by them. They can compare progress and endorse others by giving 'Kudos', the Strava equivalent of a Facebook 'like', for a completed activity. Posting comments on activities is also possible, which is another way to provide endorsing feedback to each other. Users may differ, however, in the extent to which they perceive, value and act upon the social networking features of an OFC. This likely impacts on the perceived usefulness of the OFC. We thus expect that users who are motivated more strongly to use an OFC for the social networking that it offers, i.e. users who have stronger social use motives, will also perceive OFCs as a more useful support to their work out experience:

H2: Users' social motives for OFC use positively predict perceived usefulness of this OFC

Enjoyment use motives. Lastly, in technology adoption models (e.g. Venkatesh, Thong & Xu's (2012) Unified Theory of Acceptance and Use of Technology), enjoyment or fun derived from technology use - also referred to as 'hedonic motivation' - is considered a significant factor in both technology adoption and use. Larose & Eastin (2004) refer to it as 'activity outcomes', while in Uses & Gratifications, the term 'entertainment gratifications' is used. In the context of health and fitness app use, Yuan and Kanthawala (2015) found that 'hedonic motivations' were significant predictors of users' intention of continued usage. We assume that enjoyment of OFC use will lead users to perceive it as useful in the support of their workout routine. We thus expect that:

H3: Users' enjoyment motives for OFC use will positively predict perceived usefulness of the OFC.

Perceived usefulness as a predictor of habitual OFC use

Using OFCs must deliver a perceived advantage over not using OFCs in order to foster habitual OFC use. Perceived usefulness (PU) is a fundamental concept in IT research representing this perceived advantage. Along with perceived ease of use (PEoU), it is considered to be a basic determinant of the attitude towards and intention to use technology in the Technology Acceptance Model (Davis, 1986). PU refers to the degree to which a user expects that using the technology will present an improvement over his/her present way of working. It is a concept similar to Performance Expectancy, as used in the Unified Theory of Acceptance and Use of Technology (Venkatesh, Morris, Davis, & Davis, 2003; Venkatesh, Thong, & Xu, 2012), Relative Advantage in Diffusion of Innovations (Rogers, 1995) and Outcome Expectations in Social Cognitive Theory (Bandura, 1991). In our study, OFCs are expected to deliver an added value over a situation in which no technology is used in support of physical activity through three OFC affordances: self-regulatory, social and enjoyment affordances. These affordances are assumed to shape the main use motives of OFC users.

Although OFCs can support physical activity in different ways, a prerequisite to benefiting from its potential, is that users integrate them into their physical activity routines. After all, it is only when a user regularly logs his/her activities that s/he will be able to understand patterns, to see progress and to have content around which s/he can interact with other users.

Habitual behavior has often been cited as a crucial mechanism for technology acceptance in various cases including internet use, video game attendance and mobile phone adoption (Courtois, De Grove, & De Marez, 2014; Venkatesh et al., 2012). According to LaRose & Eastin (2004), habit is ‘a form of automaticity, a pattern of behavior… that follows a fixed cognitive schema, triggered by an environmental stimulus… or by recalling a goal… and performed without further self-instruction’ (p. 363). Habitual use of OFCs would imply an automated use reflex whenever physical activity can be recorded and analyzed.

Ideally, thus, users integrate OFCs in their everyday activities to such an extent that their use becomes habitual. It is expected that users’ appreciation of the three OFC features (self-regulation, social features and enjoyment) described above plays a crucial role in whether or not a person will incorporate OFC use into his/her routine exercise behavior, via their effect on perceived usefulness. After all, if OFC use is perceived to assist in making progress in one’s exercise behavior, for example sustaining longer exercise durations, then this may trigger continued, and eventually habitual use. Hence, we expect that:

H4: Perceived usefulness of an OFC will lead to more habitual OFC use.

The Moderating Role of Use Experience

As indicated above, we distinguished three use motives of OFCs: self-regulatory, social and enjoyment motives. Users may vary in the extent to which each of these features motivates them to integrate the OFC into their everyday workout routine.

Research indicates that motives for using IT can change over time as a user's experience grows (Bhattacherjee & Premkumar, 2004; Castañeda, Muñoz-Leiva, & Luque, 2007; P. J.-H. Hu, Clark, & Ma, 2003; Venkatesh et al., 2003). This implies that the strength of motives for adopting OFCs might change as usage progresses over time.

To examine this hypothesis, we assess whether use experience, i.e. how long one has already been using an OFC, has an influence on the strength of relationships between OFC use motives, perceived usefulness and habitual OFC use.

In the case of OFC use, it is likely that factors that initially played a central role in determining the perceived usefulness of the OFC, gradually become less relevant (or vice versa). With respect to the factors examined in the current study, for instance, we may expect that users' appreciation of the self-regulatory potential of the OFC is a more important driver of perceived usefulness in the early stages of the technology adoption, because this technology adoption is likely to align with the beginning of a workout career. Particularly at the beginning of such a career, users may be more motivated to work out in order to receive (previously unknown) feedback on their performance, such as one's average running or cycling speed. For athletes with a longer OFC use experience, this type of feedback may be perceived as less 'new' or insightful, and therefore the self-regulatory feedback may contribute less to perceptions of the OFC's usefulness.

Users who have succeeded in using an OFC for a longer amount of time are likely to have gradually started to value its usage in the context of their exercise behavior. Therefore, we may assume that enjoyment of the OFC may generally become a more important driver of perceived usefulness over the course of time. Social use motives may also be more important motives of perceived usefulness for prolonged users, as these users have had more time to become central and embedded members of the online community.

To examine how use experience moderates the relationships examined, we compare the use motives of more novice users to those of experienced users. We used a data-driven procedure to assign users to either the novice or experienced user category: we considered novice users as those users who have been using an OFC for less than one year, and experienced users as those who have been using an OFC for more than one year. As indicated above, in this study, we applied our hypotheses to Strava, an OFC popular among cyclists and runners. Based on the hypotheses, a theoretical model for this study was developed (Figure 1).

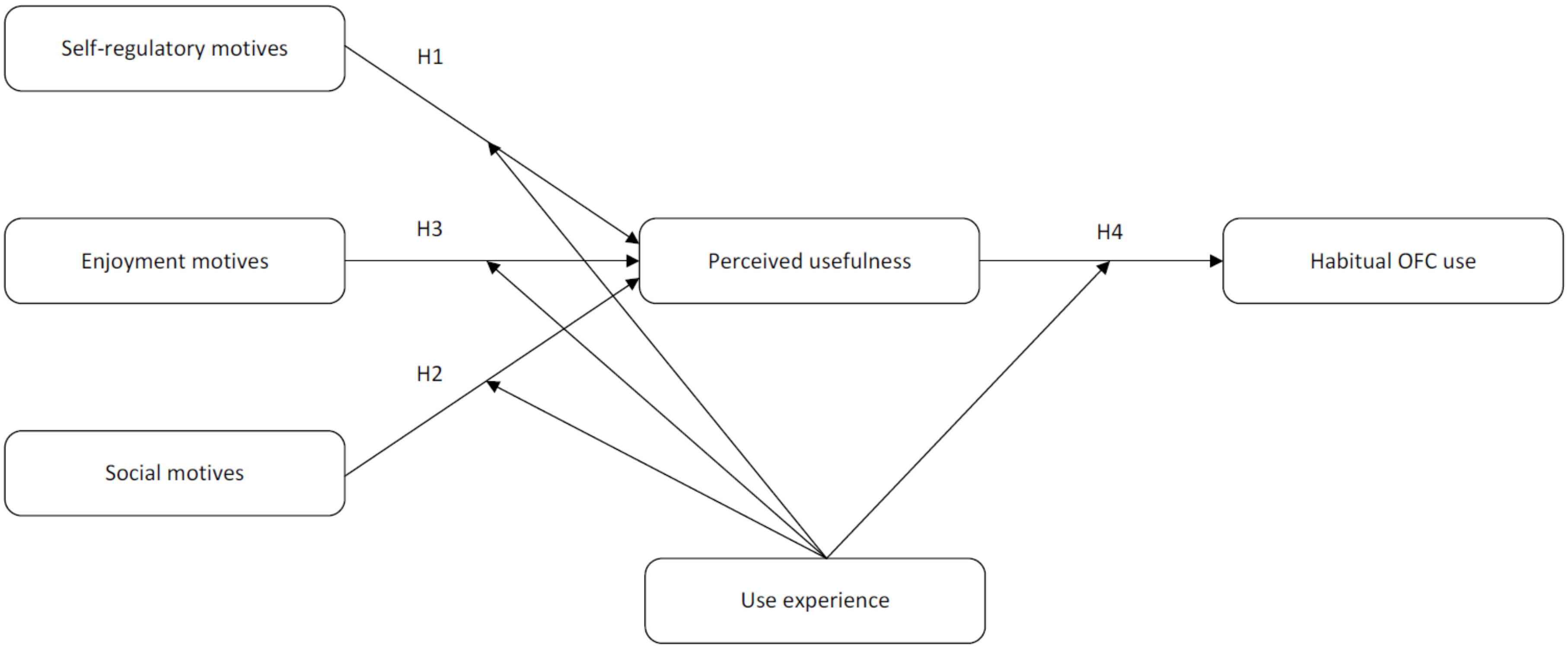

Figure 1. Theoretical model of the study

2. Methods

Procedure

A three-step recruitment procedure was followed to recruit participants for our study. First, the API of the microblogging site Twitter was used to randomly collect status updates, called tweets, containing the hashtag #Strava. Approximately 8000 tweets were collected in a one week period using the open-source solution yourTwapperkeeper as a tool for capturing tweets with the hashtag #Strava. All of these tweets contained information on the completion of a physical activity and a URL directing to the report of the corresponding activity on Strava.

Second, a custom script (programmed in the popular general-purpose scripting language PHP) extracted the Strava user id of the person who completed the activity by following the aforementioned URL to its corresponding webpage and by extracting the relevant user data from the source code of this page. This script yielded 3787 unique Strava users (no personal information such as specific names, locations, and age of users are disclosed in this study).

Third, using the Strava user id, a comment with a link to our online survey was posted beneath the user's last uploaded activity. This procedure was approved by the ethical committee of the Faculty of Social Sciences of Ghent University. Each participant was free to participate and was guaranteed that their answers would be handled in full anonymity.

Sample description

To examine our hypotheses, we conducted an online quantitative survey among Strava users. Initially, 434 Strava users completed the survey (response rate= 11.5%). To ensure that only users with recent activity on Strava were present in the sample, only those users who had uploaded an activity not later than one week prior to completion of the survey were retained. This yielded a final dataset of answers of 394 respondents. Our survey data shows that 89% of the Strava users in the sample is male. The mean age is 42 years (*SD*=10.7). Strava is mostly used for cycling (88 %) and running (55%). A majority of Strava users (85%) records their activities almost every time. Half of the respondents (49.5%) use a dedicated wearable (e.g., a sports watch or device) for recording their activities, while 40.6% usually use the Strava smartphone app.

Measures

All constructs in our model were measured on 7-point Likert scales (1=strongly disagree; 7=strongly agree) and consisted of 2 or more items. For all constructs, internal reliability was assessed using Cronbach's Alpha (Streiner, Norman, & Cairney, 2015). For the self-regulatory and social use motives, the underlying scales and items were self-constructed and carefully selected to represent the actual affordances of OFC use. To come to the final items, we first compiled a longlist of all features available on Strava. The features (e.g. checking how far one has run, checking the average heart rate on the run, selecting a race as a future goal, comparing my activities with those of others, giving likes to a friend's activity…) were grouped per use motive and consequently summarized into items for the questionnaire. All measures and corresponding items are included in Appendix A.

Self-regulatory motives. Self-regulatory motives for using Strava were assessed using a self-constructed scale of three items based on the self-regulatory, self-monitoring and goal-setting affordances available on the Strava platform (α = .82; *M* = 5.83, *SD* = 1.00; e.g. 'I use Strava… to monitor my progress').

Social motives were measured using a self-constructed scale based on the social affordances available on the Strava platform (3 items; α = .83; *M* = 4.48, *SD* = 1.39; e.g. 'I use Strava… to stay informed on my friends' activities').

Enjoyment motives. Enjoyment motives were measured using two items taken from Larose's Activity Outcomes construct (2004) (α = .60; *M* = 5.11, *SD* = 1.30; e.g. 'I use Strava… to entertain myself').

Habitual OFC use. To measure habitual OFC use, we adapted La Rose's (2004) measurement of habit (3 items; α = .68; *M* = 5.97, *SD* = 0.94; e.g. 'Uploading my activity to Strava is part of my usual exercising routine').

Perceived usefulness. Perceived usefulness was assessed by a self-constructed scale of three items regarding the perceived effectiveness of Strava use on their exercise behavior (3 items; α = .87; *M* = 5.34, *SD* = 1.21; e.g. 'Since I have been using Strava…I am more motivated to work out).

Use experience was measured by asking how long the respondent has been active on Strava on a seven-point Likert scale ranging from 'less than a month (1.5%)' over '1-3 months (7.4%), '3-6 months (11.7%)', '6-12 months (30.7%)', '1-2 years (32%)', '2-4 years (16.2%)', to '+4 years (0.5%)'.

Analyses

A multi-sample structural equation model of the theoretical model was estimated using SPSS AMOS 21. Bootstrapping was used to handle non-normality of the data (Preacher & Hayes, 2004). We based the evaluation of the fit of the model on three 'goodness-of-fit indices'. First, we report the χ^2-square. However, because the χ^2-statistic underestimates goodness of fit in analyses with large sample, we also report the χ^2/df ratio (Byrne, 2010). For large samples, a χ^2/df ratio smaller than 3.0 is considered a good or acceptable model fit. A second fit index commonly used is the Root Mean Square Error of Approximation (RMSEA). An RMSEA-value below .05 is considered a 'close fit', a value between .05 and .08 an 'acceptable fit', a value between .08 and .10 a 'mediocre' fit and a value above .10 an 'unacceptable fit' (Diamantopoulos & Siguaw, 2000; Schermelleh-Engel, Moosbrugger, & Müller, 2003). The third fit index which we report is the Comparative Fit Index (CFI), with a CFI-value above .95 indicating a 'good' fit and a value above .90 an 'acceptable' fit. Both the CFI and RMSEA are relatively unaffected by sample size (Schermelleh-Engel et al., 2003).

3. Results

Descriptive analysis

Table 1 describes the zero order correlations. As the table shows, habitual Strava use is significantly correlated to all indicators in the model. Furthermore, social motives demonstrated a significant correlation with enjoyment motives. The observation of these correlations led us to add three paths when fitting the model: a direct path from self-regulatory motives and social motives to habitual Strava use and a direct path from social motives to enjoyment motives.

Table 1

Descriptive statistics, internal reliabilities and correlations

	Mean	*S.E.*	*Alpha*	1	2	3	4	5
1. Self-regulatory motives	5.83	1.00	0,82	1				
2. Enjoyment motives	5.11	1.30	0,6	0,079	1			
3. Social motives	4.48	1.39	0,83	,125*	,438**	1		
4. Perceived usefulness	5.34	1.21	0,87	,495***	,250***	,300***	1	
5. Habitual OFC use	5.97	0.94	0,68	,441***	,209***	,313***	,431***	1

*=p<0.05;**=p<0.01;***=p<0.001 (N=394)

Model fit

An initial test of the theoretical model revealed a sub-optimal model fit (χ^2 (70) =227.55, p<0.001; χ^2/df =3.25; CFI=0.93, RMSEA=0.076). Adding the paths from self-regulatory motives and social motives to habitual Strava use and from social motives to enjoyment motives significantly improved model fit ($\Delta\chi^2(1)$ = 58.65; p<0.001). Goodness of fit indices also revealed an improved model fit (χ^2 (69)=168.90, p<0.001; χ^2/df =2.45; CFI=0.96, RMSEA=0.061).

Direct effects

Evaluation of the regressions coefficients showed significant results for all but the path from social motives to perceived usefulness. Self-regulatory motives positively predicted perceived usefulness (β= 0.52, t(69)= 9.16, p < .001; H1 supported) and also directly predicted habitual Strava use (β= 0.37, t(69)= 4.88, p <.001). Enjoyment motives positively predicted perceived usefulness (β= 0.25, t(69)= 3.06, p = .002; H3 supported). As indicated above, no significant direct relation between social motives and perceived usefulness was found (β= 0.04, t(69) = 0.60, p = .55; H2 not supported). Social motives did directly predict habitual Strava use, however (β= 0.32, t(69)=5.23, p <.001). Perceived usefulness was also found to positively predict habitual Strava use (β= 0.24, t(69)=3.40, p <.001), thus confirming H4.

Indirect effects

Subsequently, the indirect effects of self-regulatory motives, enjoyment motives and social motives on habitual Strava use though mediation of perceived usefulness were assessed. Bootstrapping was used to calculate the significance of the indirect effects. The standardized indirect effect of self-regulatory motives on habitual Strava use was .13 (p=0.003). Enjoyment motives also indirectly predicted habitual Strava use (β=0.06, p=0.012). Although social motives do not directly influence perceived usefulness, there is a significant indirect impact through mediation of enjoyment (β=0.14, p=0.01).

Use Experience Moderation

The second aim of the study was to examine the moderation of use experience. As indicated above, we considered novice users as those users who have been using an OFC for less than one year, and experienced users as those who have been using an OFC for more than one year. At the time of the study, the majority of the *novice* group (N=201) had been using Strava for three to six months (22.9%), or 6 months to a year (60.2%). In the *experienced* group (N=193), 65.8% had been using Strava one to two years and 33.2% had been using it for 2-4 years.

Experienced Strava users generally report stronger habitual Strava use than novice users (M_{novice}=5.86, *SD*=0.95; $M_{experienced}$=6.08, *SD*=0.92; *t*(392)=-2.38; *p*=.018). They also have stronger self-regulatory (M_{novice}=5.72, *SD*=1.11=; $M_{experienced}$=5.94, *SD*=0.87; *t*(378)=-2.16; *p*=.031) and social motives (M_{novice}=4.33, *SD*=1.46; $M_{experienced}$=4.65, *SD*=1.29; *t*(389)=-2.33; *p*=.021) for using Strava than novice users. No significant differences between the groups were found for enjoyment motives (M_{novice}=5.15, *SD*=1.29; $M_{experienced}$=5.07, *SD*=1.32; *t*(392)=.66; *p*=.508) and perceived usefulness (M_{novice}=5.32, *SD*=1.10; $M_{experienced}$=5.37, *SD*=1.31; *t*(392)=-.365; *p*=.716).

To control for moderation of use experience in the paths of the model, a chi-square test between the unconstrained and the fully constrained model was performed. The chi-square difference between the unconstrained (χ^2(138)= 258.86, *p*<0.001; χ^2/df=1.88; *CFI*=0.95, *RMSEA*=0.047) and fully constrained model (χ^2(154)= 285.38, *p*<0.001; χ^2/df=1.85; *CFI*=0.94, *RMSEA*=0.047) was 26.52 (df=16; *p*=0.047), confirming moderation of the model by use experience. Path by path analysis revealed only one significantly different path. More particularly, the direct path from enjoyment motives to perceived usefulness was significantly different between the groups, implying that enjoyment motives only impact significantly on perceived usefulness for experienced users. Although the parameter strength of perceived usefulness on habitual Strava use differed substantially between novice and experienced users, this difference did not reach statistical difference. The final model, with the additional paths, is presented in figure 2. Table 2 presents the results of the moderation analysis.

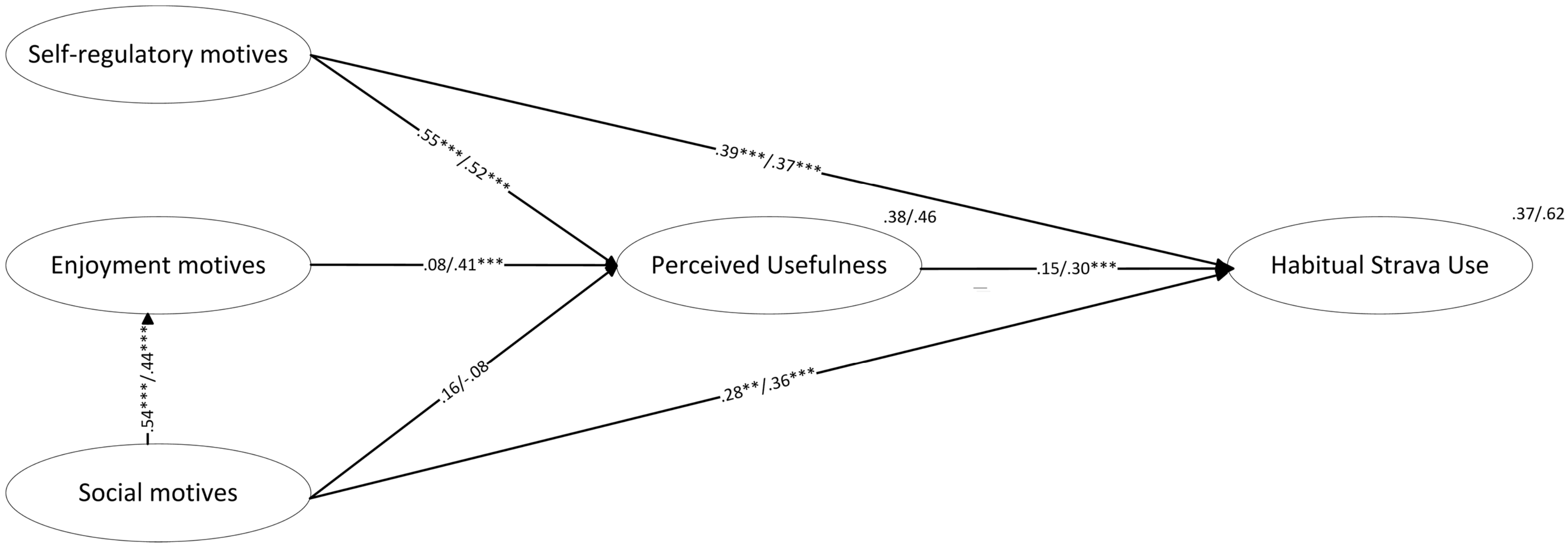

Figure 2. Multi-sample structural equation model ran for novice and experienced Strava users. Standardized coefficients are displayed, first for <1 year, second for >1 year (*=p<0.05;**=p<0.01;***=p<0.001)

Table 1.
Moderation analysis

			Novice users			Experienced users				
Causal relationship			*B*	*S.E.*	*CI*	*B*	*S.E.*	*CI*	*Difference*	*Z*
Self-Regulation	→	Perceived Usefulness	0,574***	0,084	0,351;0,807	0,702***	0,109	0,454;0,934	-0,128	0,93
Enjoyment	→	Perceived Usefulness	0,08	0,096	-0,181;0,4	0,528***	0,166	0,241;1,161	-0,448	2,342**
Social Outcomes	→	Perceived Usefulness	0,122	0,069	-0,025;0,318	-0,073	0,098	-0,356;0,135	0,195	-1,624
Perceived Usefulness	→	Habitual Strava Use	0,075	0,057	-0,077;0,25	0,12***	0,036	0,022;0,253	-0,043	0,645
Social Outcomes	→	Habitual Strava Use	0,109**	0,035	0,049;0,211	0,132***	0,031	0,079;0,209	-0,023	0,482
Self-Regulation	→	Habitual Strava Use	0,207***	0,063	0,009;0,499	0,19***	0,053	0,055;0,429	0,013	-0,164
Social Outcomes	→	Enjoyment	0,427***	0,066	0,262;0,639	0,417***	0,071	0,244;0,647	0,01	-0,103

(*=p<0.05;**=p<0.01;***=p<0.001)

4. Discussion and conclusion

Wearable technology is increasingly facilitating physiological data collection for health and wellness purposes. Data collection in itself is not the innovative part of the story, however. People have been collecting personal data for ages, with monitoring weight as an obvious example. From this point of view, the wearable itself is nothing more than a technology that facilitates more extensive and automated data collection. When the collected data add little to a person's existing knowledge, however, wearables are quickly abandoned and forgotten; it is the transformation of data into meaningful feedback that is a crucial factor for behavior change (DiClemente et al., 2001; Free et al., 2013; Owen, Fotheringham, & Marcus, 2002). This is where OFCs play their part.

Preventing drop-out can be important in promoting physical activity adherence. Therefore, identifying those factors that keep people interested in their physical activity data is crucial. This study addressed the issue by focusing on people's use of OFCs. These online platforms use data generated through wearables or fitness apps and present their users with functionalities centered around self-regulatory, social and enjoyment affordances, thus transforming data into meaningful feedback.

This study aimed, first of all, to explore the role of self-regulatory, enjoyment and social use motives in turning initial OFC use into habitual OFC use over a longer period. More specifically, we hypothesized that the relationship between self-regulatory, enjoyment and social motives and habitual OFC use would be mediated by perceived OFC usefulness. Second, we expected that self-monitoring of physical activity and exercising would be the prime mover of OFC adoption and use for novice users, while enjoyment and social affordances would become more important in later stages of use. A theoretical model was designed and applied to users of Strava, an OFC popular among cyclists and runners.

With respect to our first study aim, the findings partly supported the proposed model. Self-monitoring and enjoyment motives predicted the perceived usefulness of Strava (H1 and H3 supported), which in turn predicted habitual OFC use (H4 supported). The direct relationship between perceived usefulness and habitual Strava use implies that when a user experiences positive effects of OFC use on his/her exercise behavior, this leads to integration of OFC use into the athlete's everyday routines. With regard to self-regulatory motives, our results align with the findings of earlier studies (e.g., DiClemente et al., 2001), showing that feedback offered in the form of visualization and analysis of their data is crucial for supporting the athlete in achieving behavior change. With regard to enjoyment motives, our results support other recent work that acknowledges 'hedonic motivations' as important drivers of technology use (e.g. Yuan, Ma, Kanthawala, & Peng, 2015).

In our study, social motives did not directly, but indirectly predict perceived usefulness, through mediation of enjoyment motives (H2 not confirmed). This suggests social use motives in themselves do not make people find the OCF useful, but that they do make OFC use more enjoyable. Earlier studies have also come to the conclusion that social interaction can enhance the perceived enjoyment of technology use (Chen, Lu, & Wang, 2016; Lee & Tsai, 2010). Furthermore, self-regulatory and social motives were direct predictors of habitual Strava use, indicating the importance of these motives to the user and their role in the formation of habitual Strava use.

The second aim of the study was to ascertain whether these use motives have a different influence on the formation of habitual Strava use, depending on how long one has been using Strava. The general assumption was that self-regulatory motives would be the primary motive for novice users, while the social and enjoyment affordances of OFCs would contribute more to perceived usefulness after prolonged use. The analysis confirmed this assumption. Similar to the model before moderation, self-regulatory and social motives are direct determinants of habitual Strava use for both novice and more experienced users. Self-regulation again, which also has a strong impact on the perceived usefulness of Strava for both novice and more experienced users, appears a crucial feature for a user to make OFC use habitual. Perceived usefulness is only impacting habitual Strava use for more experienced users as it might take time for a user to recognize the effect of OFC use on their exercise behavior. Once they do, this adds significantly to habitual Strava use, as the results indicate.

Social motives on the other hand, while influencing habitual Strava use directly, don't appear to have a direct effect on perceived usefulness for both novice and experienced users. This implies that users not necessarily consider feedback from other users or the opportunity to see their peers' progress to have an impact on their own performance. Nevertheless, social outcomes do have a strong direct influence on habitual Strava use which make them a key feature that keeps users coming back to Strava. Overall, the interaction with peers on OFCs adds to the overall experience in a positive way.

When we compare novice and experienced users, it appears that people may start using OFCs for their data collection and analysis affordances, and stay if the social community aspect of the OFC offers them an enjoyable experience. Hence, in order to prevent drop-out, it seems important to create this social experience. Further research may examine this matter more closely, by investigating how social networks develop on OFCs, to what extent these online networks align with people's offline networks and why being part of such a network leads to success.

Evidently, other factors, not included in this research may also play an essential role in this regard. Perceived ease of use and self-efficacy, both in terms of being able to use the technology and to maintain a training regimen, for example, among other exercise specific factors are likely to be important. Further research should consider addressing these exercise specific factors as well.

There are limitations to the current study. First, our sampling method did likely not result in a representative sample of Strava users, in that we only approached Strava users who publicly share their results on Twitter. It is likely that social motives matter more to these users than to other users. In addition, our research is based on users of Strava, an OFC that is highly cyclist and runner oriented, but for further generalizability, it should be extended to other communities with similar or different activity focuses as Strava. The same methodology could easily be applied to similar communities focusing on different activities such as walking (Fitbit, MyFitnessPal and Fitocracy). Finally, this study uses data from those who are still active on Strava. Other studies should also focus on those who effectively quit using OFCs and wearables.

In conclusion, our research suggests that failure of apps and wearables in a physical activity context to retain users may be related in part to their inability to provide users an enjoyable online social experience in addition to the raw and informative data. The data are an important motivator, giving the users valuable feedback on their behavior, but the social affordances appear to keep them active in OFCs. Hence, efforts in the development of effective physical activity interventions using wearables or apps, need to take into account the importance of the inclusion of a user's existing (online) social network.

APPENDIX A: Constructs and items

Latent constructs	Items (totally disagree-totally agree; 1-7 scale)
Self-regulatory motives	
I use Strava…	to monitor my progress
	to follow up on my workouts
	to help me achieve my goals
Enjoyment motives	
I use Strava…	to entertain myself
	to have some fun
Social motives	
I use Strava…	to stay informed on my Strava friends' activities
	to see the progress my Strava friends are making
	to get support from others (e.g. through Likes & comments)
Perceived usefulness	
Since I have been using Strava…	I am more motivated to work out
	I work out more often
	I have more fun working out
Habitual Strava use	
	Uploading my activity to Strava is part of my usual exercising routine
	I find myself looking on Strava quite often
	I would miss Strava if it wasn't available anymore

3 DISCUSSION AND CONCLUSIONS

1. Main conclusions

This dissertation departed from the observation that despite their increasing uptake, popularity and hype status (Van der Meulen & Rivera, 2015), wearables, fitness trackers and fitness apps are fairly quickly abandoned (Clawson et al., 2015; Schneider, 2016). We attributed a major part in this issue to data analysis platforms. The main hypothesis of this thesis is that the failure of data analysis platforms to create an engaging platform that supports behavior change is due to the lack of connectivity that is offered among their users.

Two types of platforms designed to visualize, analyze and interpret the data collected with these wearables were discerned. On the one hand, there are platforms provided by wearable brands offering a wide array of features to self-regulate physical activity, set goals and work towards better health, based on data collected by a wearable of one specific brand. We named these platforms *brand-based platforms*, because they are linked to one fitness tracker (brand) only. Examples of these platforms are Garmin Connect, Polar Flow and Suunto Movescount.

On the other hand, various platforms are emerging that enable users to upload the data of various brands of fitness trackers to assist them in adopting a healthier lifestyle. The main difference with *brand-based platforms* is that the latter use a more community-based approach, focusing on social interaction between users (L. West, 2015), in addition to providing the same self-regulatory affordances of brand-based platforms. We termed these platforms ‘Online Fitness Communities’ or OFCs. Popular examples of these are Strava, RunKeeper and MyFitnessPal.

These OFCs have growing user bases and seem to succeed to achieve higher engagement of their members. It is the main assumption of this dissertation that the community-based approach, followed by these platforms, can account for this higher engagement (Taiminen, 2016). Therefore, the main objective of this thesis was ***to develop a research-based framework that unravels the underlying reasons for continued OFC use***. This framework can help us in understanding how OFCs work, and how we can translate their success to the better design of for example physical activity interventions, fitness trackers, fitness apps and their (online) data analysis platforms.

In order to build the framework, four studies were conducted in which we investigated the affordances of OFCs and how they can be linked to people's motivation to exercise. Based on Self-Determination Theory (SDT), we assume three motivations for exercise behavior: enhancing one's sense of Autonomy, Competence and Relatedness. Autonomy refers one's need to be in control of their lives and behavior. Competence is the need to feel effective or successful in our undertakings (Deci & Ryan, 2008, 2010), and Relatedness entails the need to have a meaningful relationship with significant others and one's community. A central assumption of our framework is that (online) data analysis platforms, whether *brand-based* or *OFC*, have affordances that correspond with these three basic needs. Brand-based platforms mainly have self-regulatory affordances which tap into the needs for autonomy and competence. OFCs enable these self-regulatory affordances as well, but additionally enable certain social affordances to their users, through social interaction features, which helps the users to experience a sense of relatedness to others through their exercise behavior. Based on the insights from SDT and affordances theory, we built a theoretical framework on the basis of which we deduced three empirical research questions.

The first research question aimed to unravel the role of social interaction in OFCs. This research question was addressed in studies 1 and 2. In these two studies we found that the social affordances of OFCs do enable users to support each other online. It was clear that activities, shared in OFCs, can be expected to receive endorsing comments from other OFC users. The results of study 1 further indicate that these comments are also perceived as social support by those who receive them and that they are grateful towards their peers for endorsing them. This implies that connecting recreational athletes via their activities generates interaction with social support as a result.

Study 2 focused on the practice of sharing exercise activities on other social network sites such as Facebook and Twitter. This question is relevant as sharing activities outside of the OFC can result in additional social support from for example close friends and relatives, which further addresses one's sense of relatedness. Hence, we expected to see a more substantial importance of social outcomes of sharing physical activities on social network sites (Ellison, Steinfield, & Lampe, 2007; Park, Kee, & Valenzuela, 2009). More specifically, we expected that sharing physical activities would be directed by a search for recognition and affiliation (Hsu & Lin, 2008). The findings of Study 2 however, show that this was not the case. We do expect that the results will differ depending on psychosocial characteristics of the users, for example type of runner and type of motivation.

Nevertheless, the overarching conclusions of the first two studies regarding the use of social interaction features in OFCs are that (1) they are appreciated by OFC users and (2) represent a source of social interaction and social support around people's exercise behavior, in an online environment. These conclusions are important for at least two reasons. First, while the importance of offline social support for physical activity, exercise behavior and health behavior in general was already clear from existing research, the findings of these two studies contribute to a growing body of research demonstrating the importance of *online* social support for these behaviors. Indeed, research suggests that applying social media elements in health behavior interventions yields better results (Patel, Chang, Greysen, & Chopra, 2015; Taiminen, 2016; G. Williams, M. Hamm, J. Shulhan, B. Vandermeer, & L. Hartling, 2014). Second, these insights unveil how technology is both designed and 'domesticated by the user in ways that meet the needs of (amateur) athletes in contemporary society. Indeed, exercising is increasingly done in a solitary way. This is noticeable for example in the growing popularity of individual activities such as running (Borgers et al., 2016; Scheerder & Vos, 2011). This implies that the social structures present in team sports are not available when exercising alone. With less 'offline social support' provided by exercising partners, the social interaction and resulting social support from online friends in OFCs and on social network sites, presents a potentially valuable substitute.

The second research question addressed whether OFCs effectively address the different motivations of their users through the features they offer. Our theoretical framework categorized the affordances of OFCs, enabled through their features, into self-regulatory and social affordances and linked these affordances to people's motivation to exercise. In study 3, we empirically verified this relationship between affordances and motivations by asking 360 runners who use an OFC for their motivation for running and their related OFC feature use. Our results demonstrated that OFC features are used to varying degrees depending on the athlete's motivation for running. As hypothesized in the theoretical framework, we found that the more an athlete has social motivations for running, the more social features such as commenting another athlete's activities, making new connections to other users and sharing their activities on social network sites are used. Those who are more result and competition oriented will largely keep themselves to self-regulatory features and more than others, gamification features. Hence, as affordances are only created when a user acknowledges and appreciates the usefulness of certain functionalities of IT platforms, these results imply that motivations for exercising are a prerequisite to appreciate the usefulness of a specific or corresponding OFC feature. Preferably, data analysis platforms are therefore designed in accordance with the underlying motivations of the envisioned user.

Existing research had demonstrated that wearables, fitness trackers and fitness apps are often fairly quickly abandoned after adoption (Clawson et al., 2015; Schneider, 2016) and as such, do not succeed in creating a habit of being more physically active, which is why they adopted the device in the first place. Our **third and final research question** asked whether OFCs, through their social affordances, can contribute to continued exercise behavior. To that end, we theorized that continued use of OFCs would be dependent on the level of enjoyment and engagement that is created by the data they generate (LaRose & Eastin, 2004; Venkatesh et al., 2012; Yuan et al., 2015), which is exactly where OFCs appear to excel. If data analysis platforms are more engaging and therefore used for a longer period, then indirectly, this may indirectly lead to continued exercise behavior. We hypothesized that social affordances of OFCs are a valuable tool to achieve this.

Indeed, the results of study 4, in which we surveyed both athletes who have been using an OFC for a short amount of time (i.e. 'novice' users) and athletes who have been using them for a longer amount of time ('experienced'), demonstrated that while 'novice' users primarily used OFCs for self-regulatory purposes such as self-monitoring of exercise behavior, the importance of social features appeared to be become more important for more 'experienced' users. These findings suggest that social use of OFCs can significantly contribute to the formation of habitual use, especially when regarded over the longer term.

In addition, study 4 also demonstrated that social affordances increase OFC enjoyment. Existing research (Schneider, 2016; Endeavour Partners, 2014) indicated that people who lose interest in their wearables often find them to be not engaging enough and they start to lose interest once they 'know enough' about their behavior. Our results indicate that social affordances may be a way of counteracting this trend, overcome the problem of drop-outs, and keep users engaged.

To conclude, our four studies combined provide a compelling argument for the added value of social affordances for continued OFC use. Given that OFCs operate on the basis of exercise behavior, our studies thus suggest that the social affordances inherent in OFCs play a role in supporting people in enjoying (and therefore) persisting their exercise behavior. Self-regulatory and social affordances adequately address all three of our basic needs, whereas to date, wearables, fitness trackers and fitness apps largely offer self-regulatory affordances, which address our need for competence and autonomy, yet do not frame this within a social context and thus failing to address our need for belonging.

Including social affordances in data analysis platforms may foster their continued use and also, albeit indirectly, continued exercise behavior. This knowledge can be of substantial value to both practitioners and academics.

Developers and data analysis platform designers often struggle with how to configure their platforms and how prioritize features. Academics on the other hand, are trying to assess and copy the success and impact of OFC-like platforms from different angles. Unfortunately, this often happens too fragmented and too much ad hoc. This is why an integrated lens to study and understand OFCs, which integrates behavioral motivations and technological affordances and allows to account for shifting interactions between self-regulatory and social affordances over time, is needed.

We therefore propose a refined version of the theoretical framework of this dissertation, based on the insights of the four studies, with a dual purpose for both research and development. First, it provides (academic) researchers with a means to study (wearable) technology use in a health behavior context from a motivational perspective and second, it offers researchers, designers and practitioners a 'blueprint' for developing engaging OFCs, wearables, apps, and data analysis platforms aimed at behavior change.

2. A refined theoretical framework for research and development purposes

In chapter three of this dissertation, we presented a theoretical framework that demonstrates the relationships between the basic needs as defined in SDT and OFC affordances. The framework states that to generate higher levels of engagement within platforms designed to foster behavior change, combining self-regulatory with social affordances can yield better results than self-regulatory affordances alone. The combination of these affordances implies a better addressing of the basic needs of autonomy, competence and relatedness, underlying individual self-determined behavioral choices, and constitute the theoretical core of the framework. This theoretical framework that guided the research of this dissertation is presented in figure 5.

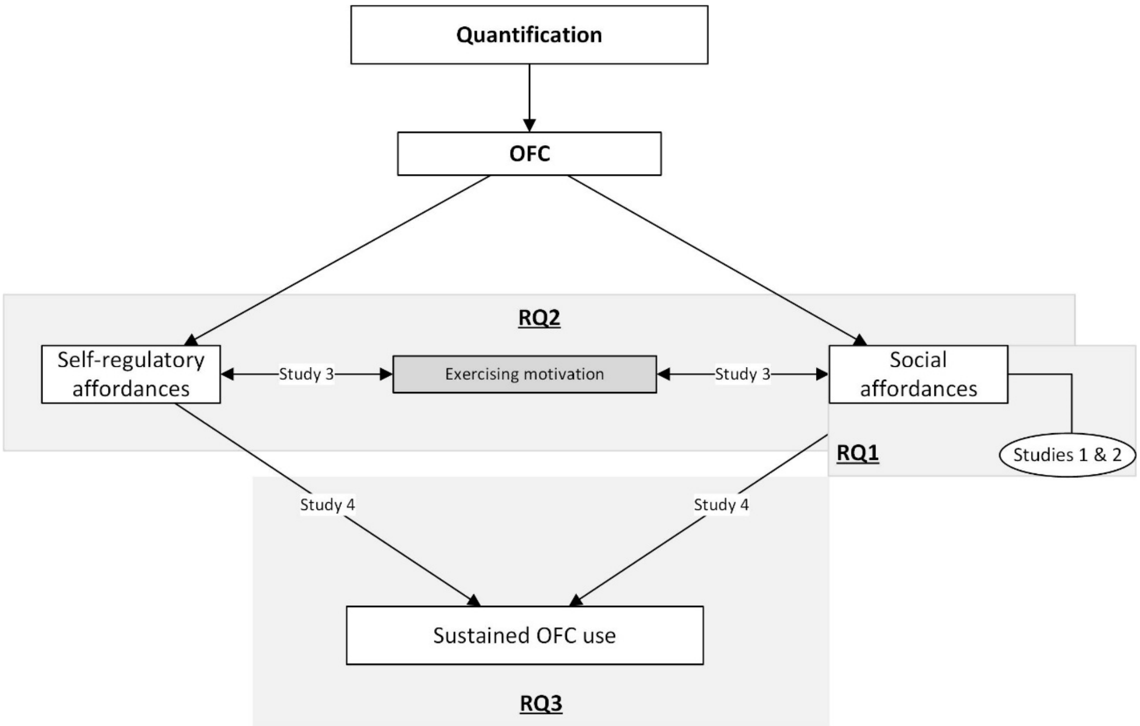

Figure 5 Theoretical framework 1.0

Our empirical investigation of the theoretical framework in the four studies that were presented in the chapters five, six and seven, has largely lead to validation of the model's core assumptions. Based on the results these four studies, we developed an enhanced model with a more practical approach for research and development purposes.

The enhanced model departs again from *quantification* of behavior: data on physical parameters are measured/captured manually, or to an increasing extent by technology. Especially the emerging market of wearable(s and) sensors have enabled this on a much larger and detailed scale. These data are increasingly used in data analysis platforms, in which various types of features aim to guide and motivate behavior(al) (change). Therefore, in contrary to the original theoretical framework presented in figure 5, the enhanced model breaks down the theoretical concept of motivational affordances into the underlying OFC features categories that afford athletes to address their basic needs of autonomy, competence and relatedness: self-regulatory, social interaction and gamification features.

The theoretical framework that is proposed is a framework to study and develop this type of platforms, to better understand and explain their use and demonstrate the inter-play between motivations, self-regulatory features, social interaction features and gamification features to foster platform engagement. Figure 6 presents this enhanced theoretical framework.

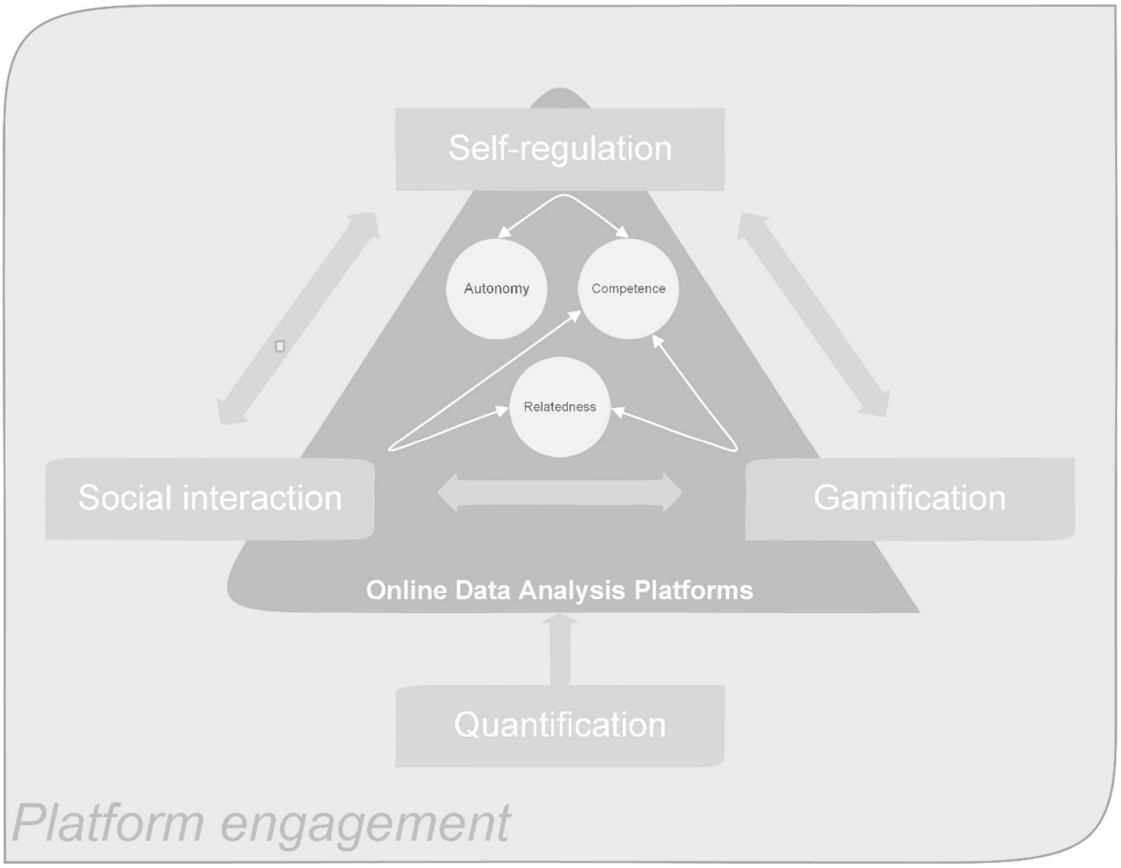

Figure 6 Theoretical framework 2.0

Self-regulatory features strengthen one's sense of competence and autonomy through mechanisms as goal-setting and self-monitoring (Bandura, 2004; Locke & Latham, 1994). Examples of these features are progress reports, calendar functions which visualize when which activity was performed and detailed activity reports in terms of heart rate, distance travelled and calories burned for example.

Social interaction features, designed to foster the provision and reception of social support, positive feedback or recognition can enforce one's sense of competence (Ryan

& Deci, 2000a) and relatedness (Deci & Ryan, 1975). Examples of these features are the opportunity to 'like' each other's activities, connect with other OFC members and give encouraging comments.

The initial theoretical framework largely focused the affordances of self-regulatory and social interaction features. Gamification features were considered to play a secondary role as a subcategory of these self-regulatory and social interaction features. Gradually however, our research demonstrated that gamification features can play a substantial role in fostering engagement and enjoyment of OFCs and afford athletes to address their basic needs of competence and relatedness (Groh, 2012). Study 3 for example, demonstrated that runners with a strong achievement motivation appreciate gamification features. Furthermore, from Study 4 we learned that enjoyment is a strong predictor of the perceived usefulness of OFCs, particularly for athletes who have been long term OFC users. Although the role of gamification features was not directly included in the model of study 3, earlier research has demonstrated the positive effect of gamification on enjoyment and engagement in IT platforms (Hamari et al., 2014; Kankanhalli, Taher, Cavusoglu, & Kim, 2012). Therefore, they are given a more prominent place in the enhanced model. Nevertheless, we consider gamification a feature category that requires more research to determine how and for whom it may be most successful, as evidence of the effectiveness of gamification is rather inconsistent (Lister et al., 2014).

Some studies suggest that the provision of external rewards could be deleterious for intrinsic motivation. Hanus & Fox (2015) for example found that in an educational context, the use of badges and leaderboards led to lower motivation and satisfaction among students and resulted in lower final exam scores. Mekler et al. (2013) however, found no evidence of this negative effect in an experimental study on the effect of badges, leaderboards and levels on autonomy and competence in an image annotation task. Their conclusion was that the implementation of features such as levels and leaderboards could be effective in promoting desired user behavior in non-game contexts (Mekler et al., 2013). Other studies also report positive effects of gamification on behavior. Hamari (2015) for example investigated the effect of handing out badges on user activity in a peer-to-peer sharing and trading market place and found that it significantly increased user transactions on the platform. Moreover, they also found that badges have a positive effect on the interaction between the users, as seen by a significant increase in the amount of comments posted. Lastly, Goh & Razikin (2015) found that gamification in 'Fitocracy' positively influenced attitude towards, enjoyment of exercising and effectively increased exercise behavior. Based on results of our studies, we believe that especially social gamification features, such as leaderboards can be effective in creating enjoyment and engagement and consequently, continued OFC use.

The three feature categories of the model should always be considered in relation to one another. Gamification uses mechanisms described under self-regulation such as goal-setting, but gamifies them by adding virtual rewards such as badges upon completion. Social interaction in its turn is essential to gamification, demonstrated in the use of leaderboards and other social comparison features in OFCs, but also in the practice of sharing achievements or *badges* on social network sites. The mutual relationship between self-regulation & social interaction is displayed in practices such as sharing exercise behavior related statuses on social network sites like Facebook and twitter, where practices of self-monitoring meet the search for social validation, support and recognition. Self-regulation, social interaction and gamification features should therefore be considered as three sides of the same coin and should not be dissociated from one another. Hence the integration of the relationships between feature categories and basic needs to study and design platforms targeted at (health) behavior (change).

3. Theoretical contributions of the framework

The framework of this dissertation offers a theoretical lens to study wearable technology and its application to physical activity from a motivational perspective as the core of the framework is shaped by the three basic needs defined by SDT: autonomy, competence and relatedness (Deci & Ryan, 1985). These needs are at the core of human behavior(al choices) and drive our motivation. For exercise behavior as well, these are the underlying needs people incessantly seek out to fulfil.

For instance, by aiming to reach self-determined goals such as running 5 kilometers, taking 10000 steps a day or becoming healthier in general, people aim to fulfil their sense of competence, of being able to achieve something they haven't achieved before. Simultaneously, they want to be in control of their behavior and experience independence in how they reach their goals. Lastly, they also want to share their achievements with peers. After all, how unsatisfying is reaching a goal and having no one to share the experience with? Within the delineated context of exercise behavior, we used Online Fitness Communities as a prime example of how a data analysis platform can tap into each of these basic needs, through both self-regulatory and social affordances. The theoretical contribution of our work is therefore threefold:

First, our research is one of the first to closely study OFCs in terms of their motivational affordances. We deconstructed OFC in terms of the features they provide and connected these, through their self-regulatory and social affordances, with the theoretical framework of Ryan and Deci's (1985) Self-Determination Theory. As such, we provided a framework to study and develop data analysis platforms, interventions, and e&mHealth applications aimed at motivating people to adopt healthier lifestyle.

Second, at the heart of the model is the focus on social affordances of technology and new media as a driving force behind motivation and engagement for exercise behavior, in addition to self-regulatory affordances. Our research demonstrates that substantial potential lies in the integration of social interaction features to develop more engaging platforms. Our research, and particularly study 3, demonstrated that specific motivations for exercise behavior active are associated with corresponding use of an OFC. Runners with social motivations for example, perceive certain OFC features as particularly useful and will use these features more than others. Furthermore, study 4 demonstrates that technology use is not always limited to the principal motivations for adopting the technology at hand. Technological characteristics or features inherent to the technology may only become of interest to a user after initial periods of use, but nevertheless, the perceived usefulness of these characteristics, may drive subsequent or continued use of the technology (Vanden Abeele, Schouten, & Antheunis, 2016). Hence, motives for using technology may change over time (Bhattacherjee & Premkumar, 2004; Castañeda et al., 2007; P. J.-H. Hu et al., 2003; Venkatesh et al., 2003). For OFCs, wearables and fitness trackers for example, social affordances may be such a driver as can be concluded from study 4. Although these social affordances will presumably never fully replace offline social interaction in the context of exercise behavior , the results of the studies conducted in this dissertation indicate that OFCs, as an emerging type of online community, can to a certain extent complement or supplement traditional exercising communities. Especially with regard to the growing trend towards individual exercise behavior (Borgers et al., 2016; Scheerder & Vos, 2011), OFCs offer opportunities to keep people connected and experience their activities together with their peers.

Lastly, this dissertation successfully joined theoretical perspectives from both new media studies and health sciences in an interdisciplinary project. We argue that the model can serve as a guide to the development and design of interventions targeted towards health behavior change interventions. Online Fitness Communities were used as an illustration or 'best practice' of how combining self-regulatory and social affordances can enhance motivation for exercise behavior. The way forward for health behavior research is to learn from these OFCs. Our theoretical framework presents a framework to guide this future research. Furthermore, our research illustrates how academic knowledge from new media studies can be applied to advance other research domains.

4. Implications of the study

Technology plays an important role in various aspects of people's daily lives. This dissertation demonstrated how (wearable) technology in combination with data analysis platforms can be applied to better motivate people to become and stay physically active. The insights obtained from this study can have various implications for society and market.

4.1 Implications for society

Contemporary society struggles with the question how technology can effectively assist people in adopting a healthier lifestyle. The current dissertation has addressed this question by examining the added value of the motivational affordances of technology. We found that while self-regulatory affordances of fitness trackers of fitness apps are valuable in the first months after adoption, social affordances can indirectly contribute to continued physical activity in the longer term. Although we did not demonstrate a direct effect of OFC use on continued exercise behavior, we did find evidence for the added value of social affordances for continued OFC use. As OFCs are mainly used for self-monitoring one's exercise behavior and therefore require the user to upload and share activities which he/she carried out him/herself, continued use of the platform can be regarded as a proxy for continued exercise behavior. Hence, the social affordances present in OFCs are likely to contribute to sustained exercise behavior.

While a trend towards healthier living can be noticed in society, adopting and sustaining a healthy lifestyle remains hard for a majority of the population. Negative consequences of unhealthy habits oftentimes only become manifest until years later, when lifestyle related diseases such as obesity become an acute health risk (e.g. in the form of diabetes). Raising awareness and assisting people to live healthier lives, in order to prevent these lifestyle related diseases is thus crucial. Technology is increasingly providing us with the means to 'quantify' ourselves and collect large amounts of data on a growing number of our health-related parameters. These 'personal informatics' provide us with valuable feedback on our health and behavior and will only continue to do so as they are further developed. However, in order to successfully apply them to achieve health behavior change, it is necessary that their motivational capabilities are further developed alongside of their technological capabilities. This thesis and related research before has illustrated that the potential of feedback can diminish when the feedback fails to incite the receiver and as such loses its motivating potential. Our framework proposes to include social affordances of technology, leveraging on the success of social media, to keep people motivated. It is however crucial in this regard that technology motivates people in a responsible way, without risking injury or overload.

4.2 Market implications

The theoretical insights of this dissertation have implications for the (wearable technology) market. Fitness trackers, smart watches, fitness apps, OFCs, Quantified Self, e&mHealth… are concepts that will receive growing attention in the coming years. We indicated the rapid abandonment of wearables as one of the basic premises of this thesis. Our research indicates that building on social affordances can yield better user retention for an OFC-related technology product. The theoretical framework can therefore serve as a guide for future development of features, OFCs, fitness trackers, data analysis platforms and fitness apps. OFCs, and especially Strava, already perform strongly on the implementation of social features. It is clear that in the timeframe during wich the research for this dissertation was ongoing, competitors have noticed the success of Strava and others OFCs, as they have and increasingly implemented social features into their platforms as well.

Based on the outcomes of this dissertation, we strongly recommend technology companies to further walk this path. Of course, if every platform offers the same social interaction features, they may represent a fading competitive advantage. The way forward for wearable technology companies is then to further develop and extend these social features in order to enhance a sense of community in their platforms. Strava, for example, is currently working on improving the interaction between members through direct messaging features which would broaden the interaction from asynchronous to (near)-synchronous. This would make communication and planning between athletes easier (Strava, 2016). Another Strava feature in this regard, is called ‘live segments’, through which an athlete can see live results of how he/she places on a segment, directly after having completed it[7]. Until recently, these efforts could only be evaluated once the activity was finished. Furthermore, Strava recently enhanced their social sharing feature, which now allows posting of a picture that marks the activity with some statistics integrated, aimed to inform the social network in a clean way. Lastly, as of December 1st

[7] A segment is a part of course, e.g. a hill climb from begin to top. On these segments, Strava users can set a time, which they can compare to those of others. The athlete with the fastest time is called the ‘King Of the Mountain’.

2016, Strava has enabled users to post other updates in addition to exercising activities in dedicated clubs. Although the feature is still in Beta, it again demonstrates Strava's focus on social interaction.

Overall, given the success of broadcasting features in social media platforms (e.g., Snapchat's stories), developers may also consider including options to broadcast a live-feed of users' physical exercise as another means to capitalize on the social embeddedness of exercise behavior. In sum, when it comes to integrating social affordances into data analysis platforms such as OFCs, it is clear that there are still several opportunities to build upon.

The development of new (social) features will be crucial for OFCs. Keeping members active on the platform is crucial from an economic perspective as this is where revenue is created, for example through premium memberships, product placement and to a certain extent, selling of the data. The success of OFCs in creating a community of athletes has not escaped the eye of large sports brands. Running shoes manufacturer Asics bought RunKeeper in 2016, while Adidas bought Runtastic in 2015 and Under Armour bought MapMyFitness, MyFitnessPal and Endomondo in 2015 (http://www.wareable.com/fitness-trackers/fitness-app-buyouts-has-anything-really-changed). Currently, Strava is the only large OFC that remains independent in the OFC landscape. It is likely that sports brands and (wearable) technology manufacturers will continue to reach out to OFCs. Automatic syncing of data collected through for example Garmin and Polar devices to Strava, Endomondo… illustrates how OFCs have become ‘incontournable’ for technology manufacturers. As much as they (presumably) would like to create a similar community among their customers on their own ‘brand-based’ platforms, it seems that OFCs may have already taken the field.

Apart from the importance of social affordances, our research has also indicated that the features of OFCs cannot be considered as a generic ‘one size fits all’ offer. Study 4 of this thesis illustrated that OFCs are initially largely used for self-monitoring purposes, while after some time, social interaction features become more intensively used and appreciated. Study 3 illustrated how users with different motivations for running (e.g. weight loss versus competition) prefer to use other features. These findings tie in with the findings of earlier research. Previous studies, for example, already suggested that gamification features are not desirable for specific types of users (Akasaki et al., 2016; Karanam et al., 2014). Therefore, we suggest that designers work on the idea of a building modular platform, in which a user is capable of adding and ignoring platform features in accordance with his/her motivations, intentions, goals and preferences. A user should be able to enable features whenever he/she considers them to be of value. When one is reluctant towards competitive features such as leaderboards for example, one should be able to enclose these or replace them with for example extensions of features they do appreciate. This could however also occur automatically. Machine-learning algorithms for example could detect when certain features could become of interest to a user and consequently be proposed or added to his/her modular profile page.

5. Limitations and further research

Although this dissertation makes an important contribution to the fields of media studies and health behavior by unveiling the added value of the social affordances in OFCs, it is important to reflect on what could have been better and provide suggestions for further research.

First of all, this dissertation strongly focused on the use of OFCs by its existing members. By focusing on the behavior of this population, we aimed to demonstrate how certain types of features that are currently only to a limited extent offered in most online data analysis platforms can aid in creating a higher engagement on the platform and as such, indirectly help them to maintain their exercise behavior.

This implies however, that we did not study how these features or OFCs can be employed to encourage inactive people to become more physically active. We therefore did not focus on the phases preceding the take up of exercise behavior, but rather on the phases in which this has already happened. In terms of the Transtheoretical Model of behavior change (Prochaska & Velicer, 1997), we focused our research on the 'action' and 'maintenance' phases, rather than the 'precontemplation', 'contemplation' and 'preparation' phase. In other words, the focus of our studies lay on how OFCs can support those who have started to exercise to keep up their motivation. We suggest that future research further builds on the findings of this dissertation to assess how the theoretical framework can be used in earlier stages of behavior change. The promise of behavioral feedback, made by most fitness tracker manufacturers, is an important starting point, as our studies suggested that the main reasons for people to start using a fitness tracker and/or an OFC are self-monitoring purposes. The theoretical model of this dissertation then suggests how social affordances can be useful to keep up motivation once people have actually started to change their behavior.

Second, a critical reflection on the population addressed in the four studies of this dissertation is necessary. In studies 1, 2 and 4, the population studied consisted solely of Strava users. In study 4, a broader population was used comprising users of Strava, RunKeeper, Polar Flow, Garmin Connect, Endomondo and Runtastic. The population of these studies undeniably have specific characteristics which may have impacted the results and conclusions of this dissertation. First of all, they are already engaged in exercise behavior and may have already incorporated this into their daily lives as a habit. Furthermore, they were also already present on an OFC at the time the studies were conducted. This implies that they already had (intrinsic or extrinsic) motivations for engaging in exercise behavior and using an OFC. For Strava users in particular for example, competition is a more pronounced motivator to exercise than RunKeeper users for example.

Furthermore, the socio-demographic characteristics of OFC user's does not reflect the general population, nor does it reflect certain physical activity risk groups. The Strava user base for example, consists of predominantly higher educated males. Consequently, if we want to make recommendations on how to deploy the insights of our studies to promote exercise behavior in a general population of specific risk groups, we have to keep in mind that those who are currently using OFCs may not be the people we want or need to reach with interventions for example. Those who are at risk for lifestyle related health conditions such as Type 2 diabetes and cardiovascular diseases are likely not to be among current OFC users. Therefore, giving recommendations based on the results of our studies towards the development of interventions targeted at risk groups that socio-demographically and psychosocially significantly differ from the population used in our studies, must be done with the necessary precaution.

Moreover, people who have privacy issues with regard to sharing personal data online, are likely to have lower intention to use wearables and their accompanying online data analysis platforms and would therefore be less inclined to use OFCs. When developing digital interventions or online data analysis platforms, taking the privacy of the intended user into account throughout the whole development, often termed 'privacy by design', may present an approach that addresses this issue and could possibly lead to increased confidence in privacy-sensitive groups.

Third, our model in its current form does not discern between the needs of specific segments in the general population. While the model suggests that data analysis platforms should include self-regulatory, social and gamification features to optimally support motivation, it is possible for example that leaderboards are perceived as too competitive certain segments and that they prefer a more cooperative type of gamification. Therefore, further research is needed into which features are appealing and effective for which segment and how they should be provided. Study 3 of this dissertation applied this question to the population of Flemish runners who use an OFC. Future research should focus on addressing the same question in other populations, and risk groups in particular, to assess how they experience the use of these features, to what extent they appreciate these features and how effective they are at creating both a higher platform engagement and exercise behavior. Similarly, while study 3 mainly focused on connecting the affordances to motivations on the total sample, socio-demographic characteristics of the research subject such as gender, may result in an even more diverging result.

All of the issues regarding the population used in our studies may have influenced the results to some extent and limit their generalizability. Although further research should be conducted to demonstrate the potential of social and gamification features to enhance platform engagement in other populations than those used in our studies, we expect that the social affordances of these features will appeal to a broader population. The basis of this hypothesis is the foundation of our theoretical model in Self-Determination theory and the especially the universal need for belonging on the on hand and the success of social media platforms in general, in which the same social affordances can be found, experienced and appreciated by their users. It is no coincidence that among the top five downloaded apps on the iPhone, four are social apps (Snapchat(1), Messenger(2), Instagram(4) and Facebook(5)) (Eadicicco, 2016).

Third, as new media scholars, we primarily focused on conducting research into **persisted OFC use**. As a result, in none of the empirical studies, exercise behavior was directly measured. We can however, with a certain confidence, say that OFC use indirectly involves exercise behavior. After all, using an OFC without uploading activities does not provide substantial added value.

Fourth, and related to the former, this thesis does not represent an impact or effects study of social and self-regulatory affordances on actual motivation and behavior. Indeed, the main objective of this thesis was to ***develop and empirically validate a research-based framework that unravels the underlying reasons for continued OFC use***. While impact or effect studies should definitely be performed in further research, it laid beyond the scope of this thesis a dissertation in social science. We are confident, however, that our framework now delivers a tool to guide future research, in which impact and effectiveness studies should unquestionably be conducted.

Fifth, we believe that there is a vast opportunity for further examination of social and gamification features in data analysis platforms for personal informatics. Our work limited itself to describe and study the existing features, but future research should further look into how innovative features can be developed and applied to enhance people's motivation. Our framework, with self-determined behavior at its core, presents a valuable starting point for research into which features tap into which basic needs and as such can be applied to enhance one's motivation. This also implies further research into improved visualization and presentation of data to enable people to effortlessly make sense of their data.

Sixth, we recommend that behavioral data take a more prominent place in future research. Our research, while focused on large data collection through wearable technology, still largely depended on self-reported data. Wearables and data analysis platforms generate enormous amounts of data that could be of significant value for future research. Logging continuous use of wearables and OFCs for example, represents a (nearly) non-intrusive opportunity to study physical activity of which we could have taken more advantage of. Digital methods to analyze these new sources of data, although having considerable drawback such as representativity, will become more important in addition to traditional methods and should be explored for research into physical activity.

Lastly, we believe that our theoretical framework can serve as a tool to guide similar research in related research domains such as behavioral nutrition and sustainable energy use. Wearable technology is increasingly offering the technological means to quantify such behavior. These data can be presented back to users/consumers in a manner that structured as proposed in our theoretical framework. As such, we apply these quantified data about for example our eating patterns or residential energy use to promote healthier food intake or encourage responsible residential energy use in a data analysis platform that motivates us through both self-regulatory and social affordances.

4 REFERENCES

Acquisti, A., & Gross, R. (2006). Imagined Communities: Awareness, Information Sharing, and Privacy on the Facebook. In G. Danezis & P. Golle (Eds.), *Privacy Enhancing Technologies: 6th International Workshop, PET 2006, Cambridge, UK, June 28-30, 2006, Revised Selected Papers* (pp. 36-58). Berlin, Heidelberg: Springer Berlin Heidelberg.

Aittasalo, M., Miilunpalo, S., Kukkonen-Harjula, K., & Pasanen, M. (2006). A randomized intervention of physical activity promotion and patient self-monitoring in primary health care. *Preventive Medicine, 42*(1), 40-46. doi:http://dx.doi.org/10.1016/j.ypmed.2005.10.003

Akasaki, H., Suzuki, S., Nakajima, K., Yamabe, K., Sakamoto, M., Alexandrova, T., & Nakajima, T. (2016). One Size Does Not Fit All: Applying the Right Game Concepts for the Right Persons to Encourage Non-game Activities. In S. Yamamoto (Ed.), *Human Interface and the Management of Information: Applications and Services: 18th International Conference, HCI International 2016 Toronto, Canada, July 17-22, 2016. Proceedings, Part II* (pp. 103-114). Cham: Springer International Publishing.

Almeida, F. (2008). *The relationship between social networks, social support, physical activity and self-rated health: An exploratory study* (J. M. Jenson Ed. Vol. 3297592). Ann Arbor: University of Denver.

Almeida, T. (2015). *Designing intimate wearables to promote preventative health care practices*. Paper presented at the 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, Osaka, Japan.

Anderson-Bill, E. S., Winett, R. A., & Wojcik, J. R. (2011). Social cognitive determinants of nutrition and physical activity among web-health users enrolling in an online intervention: the influence of social support, self-efficacy, outcome expectations, and self-regulation. *Journal of Medical Internet Research, 13*(1). doi: 10.2196/jmir.1551

Anderson, E. S., Winett, R. A., & Wojcik, J. R. (2007). Self-regulation, self-efficacy, outcome expectations, and social support: social cognitive theory and nutrition behavior. *Annals of Behavioral Medicine, 34*(3), 304-312.

Anderson, E. S., Wojcik, J. R., Winett, R. A., & Williams, D. M. (2006). Social-cognitive determinants of physical activity: The influence of social support, self-efficacy, outcome expectations, and self-regulation among participants in a church-based health promotion study. *Health Psychology, 25*(4), 510-520.

Anderssen, N., & Wold, B. (1992). Parental and peer influences on leisure-time physical activity in young adolescents. *Research Quarterly for Exercise and Sport, 63*(4), 341-348.

Arthur, C. (2014). Wearables: one-third of consumers abandoning devices. Retrieved from https://www.theguardian.com/technology/2014/apr/01/wearables-consumers-abandoning-devices-galaxy-gear

Arthur, D. (2014). First look: new Garmin Connect. Retrieved from http://road.cc/content/news/118829-first-look-new-garmin-connect

Ashcroft, S. (2015). Polar Flow updated with open water swimming and social features. Retrieved from http://www.wareable.com/polar/polar-flow-app-update-swimming-features-1366

Baek, K., Holton, A., Harp, D., & Yaschur, C. (2011). The links that bind: Uncovering novel motivations for linking on Facebook. *Computers in Human Behavior, 27*(6), 2243-2248. doi:http://dx.doi.org/10.1016/j.chb.2011.07.003

Balatsoukas, P., Kennedy, C. M., Buchan, I., Powell, J., & Ainsworth, J. (2015). The Role of Social Network Technologies in Online Health Promotion: A Narrative Review of Theoretical and Empirical Factors Influencing Intervention Effectiveness. *J Med Internet Res, 17*(6), e141. doi:10.2196/jmir.3662

Bandura, A. (1977). Self-efficacy: toward a unifying theory of behavioral change. *Psychological review, 84*(2), 191-215. doi:http://dx.doi.org/10.1037/0033-295X.84.2.191

Bandura, A. (1991). Social cognitive theory of self-regulation. *Organizational behavior and human decision processes, 50*(2), 248-287. doi:http://dx.doi.org/10.1016/0749-5978(91)90022-L

Bandura, A. (2004). Health promotion by social cognitive means. *Health Education & Behavior, 31*(2), 143-164.

Bandura, A., & Cervone, D. (1983). Self-evaluative and self-efficacy mechanisms governing the motivational effects of goal systems. *Journal of Personality and social Psychology, 45*(5), 1017-1028.

Bandura, A., & Schunk, D. (1981). Cultivating competence, self-efficacy, and intrinsic interest through proximal self-motivation. *Journal of Personality and social Psychology, 41*(3), 586-598.

Barghava, T. (2016). What Fueled Runkeeper's Growth Engine? Growth Hacking, May be? Retrieved from http://www.appvirality.com/blog/runkeeper-growth-hacking/

Barrett, M. A., Humblet, O., Hiatt, R. A., & Adler, N. E. (2013). Big data and disease prevention: From quantified self to quantified communities. *Big Data, 1*(3), 168-175. doi:10.1089/big.2013.0027

Beachboard, M. R., Beachboard, J. C., Li, W., & Adkison, S. R. (2011). Cohorts and Relatedness: Self-Determination Theory as an Explanation of How Learning Communities Affect Educational Outcomes. *Research in Higher Education, 52*(8), 853-874. doi:10.1007/s11162-011-9221-8

Beets, M. W., Cardinal, B. J., & Alderman, B. L. (2010). Parental social support and the physical activity-related behaviors of youth: A review. *Health Education & Behavior, 37*(5), 621-644.

Bender, T. (1978). *Community and Social Change in America*. New Brunswick, NJ: Rutgers University Press.

Bessell, T. L., McDonald, S., Silagy, C. A., Anderson, J. N., Hiller, J. E., & Sansom, L. N. (2002). Do Internet interventions for consumers cause more harm than good? A systematic review. *Health Expectations, 5*(1), 28-37.

Bhattacherjee, A., & Premkumar, G. (2004). Understanding Changes in Belief and Attitude toward Information Technology Usage: A Theoretical Model and Longitudinal Test. *MIS quarterly, 28*(2), 229-254. doi:10.2307/25148634

Borgers, J., Pilgaard, M., Vanreusel, B., & Scheerder, J. (2016). Can we consider changes in sports participation as institutional change? A conceptual framework. *International Review for the Sociology of Sport*, 1012690216639598.

Boticki, I., Baksa, J., Seow, P., & Looi, C.-K. (2015). Usage of a mobile social learning platform with virtual badges in a primary school. *Computers & Education, 86*(12), 120-136.

Boyd, D., & Ellison, N. (2007). Social Network Sites: Definition, History, and Scholarship. *Journal of Computer-Mediated Communication, 13*(1), 210-230. doi:10.1111/j.1083-6101.2007.00393.x

Boyd, D., Golder, S., & Lotan, G. (2010). *Tweet, tweet, retweet: Conversational aspects of retweeting on twitter.* Paper presented at the 43rd International Conference on System Sciences (HICSS), Kauai, HI.

Braithwaite, D. O., Waldron, V. R., & Finn, J. (1999). Communication of social support in computer-mediated groups for people with disabilities. *Health communication, 11*(2), 123-151.

Bravata, D. M., Smith-Spangler, C., Sundaram, V., & et al. (2007). Using pedometers to increase physical activity and improve health: A systematic review. *Jama, 298*(19), 2296-2304. doi:10.1001/jama.298.19.2296

Broekhuizen, K., Kroeze, W., van Poppel, M. N., Oenema, A., & Brug, J. (2012). A systematic review of randomized controlled trials on the effectiveness of computer-tailored physical activity and dietary behavior promotion programs: an update. *Annals of Behavioral Medicine, 44*(2), 259-286.

Buning, R., & Walker, M. (2016). Differentiating Mass Participant Sport Event Consumers: Traditional Versus Non-Traditional Events. *Sport Marketing Quarterly, 25*(1), 47-58.

Burns, P., Lueg, C., & Berkovsky, S. (2012). *Empower everybody - designing persuasive wearable technology for user empowerment.* Paper presented at the 2nd International Workshop: The Body in Design, Melbourne, Victoria, Australia.

Byrne, B. (2010). *Structural equation modeling with AMOS: Basic concepts, applications, and programming* (2nd ed.). New York: Routledge.

Calvo, T. G., Cervelló, E., Jiménez, R., Iglesias, D., & Murcia, J. A. M. (2010). Using self-determination theory to explain sport persistence and dropout in adolescent athletes. *The Spanish Journal of Psychology, 13*(02), 677-684.

Castañeda, J. A., Muñoz-Leiva, F., & Luque, T. (2007). Web Acceptance Model (WAM): Moderating effects of user experience. *Information & Management, 44*(4), 384-396. doi:http://dx.doi.org/10.1016/j.im.2007.02.003

Castells, M. (2011). *The rise of the network society: The information age: Economy, society, and culture* (Vol. 1): John Wiley & Sons.

Cavallo, D., Tate, D., Ries, A., Brown, J., DeVellis, R., & Ammerman, A. (2012). A Social Media–Based Physical Activity Intervention: A Randomized Controlled Trial. *American journal of preventive medicine, 43*(5), 527-532. doi:http://dx.doi.org/10.1016/j.amepre.2012.07.019

Cavallo, D., Tate, D., Ward, D., DeVellis, R., Thayer, L., & Ammerman, A. (2014). Social support for physical activity—role of Facebook with and without structured intervention. *Translational Behavioral Medicine, 4*(4), 346-354. doi:10.1007/s13142-014-0269-9

Chen, A., Lu, Y., & Wang, B. (2016). Enhancing perceived enjoyment in social games through social and gaming factors. *Information Technology & People, 29*(1), 99-119. doi:doi:10.1108/ITP-07-2014-0156

Chiu, C.-M., Wang, E. T., Shih, F.-J., & Fan, Y.-W. (2011). Understanding knowledge sharing in virtual communities: an integration of expectancy disconfirmation and justice theories. *Online Information Review, 35*(1), 134-153.

Chouffani, R. (2011). The different types of mobile healthcare apps. Retrieved from http://searchhealthit.techtarget.com/healthitexchange/meaningfulhealthcareinformaticsblog/the-different-types-of-mobile-healthcare-apps/

Cialdini, R. B. (2009). *Influence: Science and practice* (Vol. 4). Boston: Pearson Education.

Clawson, J., Pater, J. A., Miller, A. D., Mynatt, E. D., & Mamykina, L. (2015). *No longer wearing: investigating the abandonment of personal health-tracking technologies on craigslist*. Paper presented at the Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Osaka, Japan.

Cobb, N. K., & Graham, A. L. (2012). Health Behavior Interventions in the Age of Facebook. *American journal of preventive medicine, 43*(5), 571-572. doi:http://dx.doi.org/10.1016/j.amepre.2012.08.001

Cobb, S. (1976). Social support as a moderator of life stress. *Psychosomatic medicine, 38*(5), 300-314.

Cole, F. L. (1988). Content analysis: process and application. *Clinical Nurse Specialist, 2*(1), 53-57.

Coleman, P. K., & Karraker, K. H. (2003). Maternal self-efficacy beliefs, competence in parenting, and toddlers' behavior and developmental status. *Infant Mental Health Journal, 24*(2), 126-148.

Colvin, J., Chenoweth, L., Bold, M., & Harding, C. (2004). Caregivers of Older Adults: Advantages and Disadvantages of Internet-based Social Support*. *Family Relations, 53*(1), 49-57.

Conroy, D. E., Yang, C.-H., & Maher, J. P. (2014). Behavior change techniques in top-ranked mobile apps for physical activity. *American journal of preventive medicine, 46*(6), 649-652.

Conroy, M. B., Yang, K., Elci, O. U., Gabriel, K. P., Styn, M. A., Wang, J., . . . Burke, L. E. (2011). Physical activity self-monitoring and weight loss: 6-month results of the SMART trial. *Med Sci Sports Exerc, 43*(8), 1568-1574. doi:10.1249/MSS.0b013e31820b9395

Consolvo, S., Everitt, K., Smith, I., & Landay, J. A. (2006). *Design requirements for technologies that encourage physical activity*. Paper presented at the Proceedings of the SIGCHI Conference on Human Factors in Computing Systems, Montréal, Québec, Canada.

Cooke, B. D., Rossmann, M. M., McCubbin, H. I., & Patterson, J. M. (1988). Examining the Definition and Assessment of Social Support: A Resource for Individuals and Families. *Family Relations, 37*(2), 211-216. doi:10.2307/584322

Coulson, N. (2005). Receiving social support online: an analysis of a computer-mediated support group for individuals living with irritable bowel syndrome. *CyberPsychology & Behavior, 8*(6), 580-584.

Courtois, C., De Grove, F., & De Marez, L. (2014). The role of socio-spatial context in the habit–goal interface of audiovisual media consumption. *POETICS, 45*(0), 1-18. doi:http://dx.doi.org/10.1016/j.poetic.2014.05.002

Courtois, C., Mechant, P., & De Marez, L. (2011). Teenage uploaders on YouTube: networked public expectancies, online feedback preference, and received on-platform feedback. *Cyberpsychology, Behavior, and Social Networking, 14*(5), 315-322.

Cullen, K. W., Baranowski, T. O. M., & Smith, S. P. (2001). Using goal setting as a strategy for dietary behavior change. *Journal of the American Dietetic Association, 101*(5), 562-566. doi:http://dx.doi.org/10.1016/S0002-8223(01)00140-7

Cutrona, C. E., & Suhr, J. A. (1992). Controllability of stressful events and satisfaction with spouse support behaviors. *Communication Research, 19*(2), 154-174.

Dahlem, N. W., Zimet, G. D., & Walker, R. R. (1991). The multidimensional scale of perceived social support: A confirmation study. *Journal of clinical psychology, 47*(6), 756-761.

Davis, F. (1986). *A technology acceptance model for empirically testing new end-user information systems: Theory and results.* Massachusetts Institute of Technology.

Deci, E. (2002). Overview of self-determination theory: An organismic dialectical perspective *Handbook of self-determination research* (pp. 3-33): University of Rochester Press.

Deci, E., & Ryan, R. (1975). *Intrinsic motivation*: Wiley Online Library.

Deci, E., & Ryan, R. (1985). Cognitive evaluation theory: Intrinsic motivation and self-determination in human behavior (pp. 43-85): Springer.

Deci, E., & Ryan, R. (2002). *Handbook of Self-determination Research*. Rochester: University of Rochester Press.

Deci, E., & Ryan, R. (2008). Self-determination theory: A macrotheory of human motivation, development, and health. *Canadian Psychology/Psychologie canadienne, 49*(3), 182-185. doi:10.1037/a0012801

Deci, E., & Ryan, R. (2010). Self-Determination *The Corsini Encyclopedia of Psychology*: John Wiley & Sons, Inc.

Deci, E., & Vansteenkiste, M. (2004). Self-determination theory and basic need satisfaction: Understanding human development in positive psychology. *Ricerche di Psicologia, 27*(1), 23-40.

Delaney, B. (2013). Inside: Strava's San Francisco studio. Strava doubles user base in 2013, targets global growth in 2014. Retrieved from http://www.bikeradar.com/road/gear/article/inside-stravas-san-francisco-studio-39313/

DeSanctis, G., & Poole, M. S. (1994). Capturing the complexity in advanced technology use: Adaptive structuration theory. *Organization Science, 5*(2), 121-147.

Deterding, S. (2011, May 7–12). *Situated motivational affordances of game elements: A conceptual model.* Paper presented at the CHI 2011 workshop: Gamification: Using game design elements in non-gaming contexts, Vancouver, BC, Canada.

Deterding, S., Dixon, D., Khaled, R., & Nacke, L. (2011). *From game design elements to gamefulness: defining "gamification"*. Paper presented at the Proceedings of the 15th International Academic MindTrek Conference: Envisioning Future Media Environments, Tampere, Finland.

Dholakia, U. M., Bagozzi, R. P., & Pearo, L. K. (2004). A social influence model of consumer participation in network-and small-group-based virtual communities. *International journal of research in marketing, 21*(3), 241-263.

Diamantopoulos, A., & Siguaw, J. A. (2000). *Introducing LISREL*. London, England: SAGE Publications, Ltd.

DiClemente, C. C., Marinilli, A. S., Singh, M., & Bellino, L. E. (2001). The role of feedback in the process of health behavior change. *American Journal of Health Behavior, 25*(3), 217-227. doi:10.5993/AJHB.25.3.8

Dijkstra, P., Kuyper, H., van der Werf, G., Buunk, A. P., & van der Zee, Y. G. (2008). Social Comparison in the Classroom: A Review. *Review of Educational Research, 78*(4), 828-879. doi:10.3102/0034654308321210

DiLorenzo, T. M., Bargman, E. P., Stucky-Ropp, R., Brassington, G. S., Frensch, P. A., & LaFontaine, T. (1999). Long-Term Effects of Aerobic Exercise on Psychological Outcomes. *Preventive Medicine, 28*(1), 75-85. doi:http://dx.doi.org/10.1006/pmed.1998.0385

Dishman, R. K., Sallis, J. F., & Orenstein, D. R. (1985). The determinants of physical activity and exercise. *Public health reports, 100*(2), 158-171.

Dredge, S. (2013, September 23). RunKeeper talks smart watches, iPhone 5s and privacy issues for fitness apps. *The Guardian*. Retrieved from http://www.theguardian.com

Eadicicco, L. (2016). These Are the Most Popular iPhone Apps of 2016. Retrieved from http://time.com/4592864/most-popular-iphone-apps-2016/

Edmondson, R. (2003). Social capital: a strategy for enhancing health? *Social Science & Medicine, 57*(9), 1723-1733.

Edwards, B. (2014). Strava: Apps, KOM's and the Future of Your Ride Data. Retrieved from http://pelotonmagazine.com/goods/strava-apps-koms-and-the-future-of-your-ride-data/

Eime, R. M., Young, J. A., Harvey, J. T., Charity, M. J., & Payne, W. R. (2013). A systematic review of the psychological and social benefits of participation in sport for children and adolescents: informing development of a conceptual model of health through sport. *International Journal of Behavioral Nutrition and Physical Activity, 10*(1), 98. doi:10.1186/1479-5868-10-98

Ellison, N. B., Steinfield, C., & Lampe, C. (2007). The Benefits of Facebook "Friends:" Social Capital and College Students' Use of Online Social Network Sites. *Journal of*

Computer-Mediated Communication, 12(4), 1143-1168. doi:10.1111/j.1083-6101.2007.00367.x

Ellison, N. B., Steinfield, C., & Lampe, C. (2011). Connection Strategies: Social Capital Implications of Facebook-enabled Communication Practices. *New Media & Society*. doi:10.1177/1461444810385389

Elo, S., & Kyngäs, H. (2008). The qualitative content analysis process. *Journal of advanced nursing, 62*(1), 107-115.

Endeavour Partners. (2014). Inside Wearables: How the Science of Human Behavior Change Offers the Secret to Long-Term Engagement (pp. 17).

Epstein, D. A., Ping, A., Fogarty, J., & Munson, S. A. (2015). *A lived informatics model of personal informatics*. Paper presented at the Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Osaka, Japan.

Ferguson, H. (2014). The Killer App for Wearables Won't Be Fitness or Health -Think Wallet. Retrieved from https://www.wired.com/insights/2014/07/killer-app-wearables-wont-fitness-health-think-wallet/

Foster, D., Linehan, C., Kirman, B., Lawson, S., & James, G. (2010). *Motivating physical activity at work: using persuasive social media for competitive step counting*. Paper presented at the 14th International Academic MindTrek Conference: Envisioning Future Media Environments, Tampere, Finland. http://dl.acm.org/citation.cfm?id=1930510

Free, C., Phillips, G., Galli, L., Watson, L., Felix, L., Edwards, P., . . . Haines, A. (2013). The effectiveness of mobile-health technology-based health behaviour change or disease management interventions for health care consumers: a systematic review. *PLoS Med, 10*(1), e1001362.

Gagné, M., & Deci, E. (2005). Self-determination theory and work motivation. *Journal of organizational Behavior, 26*(4), 331-362.

Garber, C., Blissmer, B., Deschenes, M., Franklin, B., Lamonte, M., Lee, I., . . . Swain, D. (2011). American College of Sports Medicine position stand. Quantity and quality of exercise for developing and maintaining cardiorespiratory, musculoskeletal, and neuromotor fitness in apparently healthy adults: guidance for prescribing exercise. *Medicine and science in sports and exercise, 43*(7), 1334-1359.

Gardner, B., Lally, P., & Wardle, J. (2012). Making health habitual: the psychology of 'habit-formation' and general practice. *The British Journal of General Practice, 62*(605), 664-666. doi:10.3399/bjgp12X659466

GET search/tweets. (2013). Retrieved from https://dev.twitter.com/docs/api/1.1/get/search/tweets

Gibson, J. J. (2014). *The ecological approach to visual perception: classic edition*. New York: Psychology Press.

Giddens, A. (1991). *Modernity and self-identity: Self and society in the late modern age*. Stanford, CA: Stanford University Press.

Gisle, L., & Demarest, S. (2013). *Gezondheidsenquête 2013. Rapport 2: Gezondheidsgedrag en Leefstijl. Samenvatting van de onderzoeksresultaten*. Retrieved from Wetenschappelijk Instituut Volksgezondheid: https://his.wiv-isp.be/nl/Gedeelde%20%20documenten/summ_LS_NL_2013.pdf

A Global Data Set. (2014). Retrieved from Labs.strava.com

Glynn, L. G., Hayes, P. S., Casey, M., Glynn, F., Alvarez-Iglesias, A., Newell, J., . . . Murphy, A. W. (2014). Effectiveness of a smartphone application to promote physical activity in primary care: the SMART MOVE randomised controlled trial. *British Journal of General Practice, 64*(624), e384-e391. doi:10.3399/bjgp14X680461

Goh, D. H.-L., & Razikin, K. (2015). Is Gamification Effective in Motivating Exercise? In M. Kurosu (Ed.), *Human-Computer Interaction: Interaction Technologies: 17th International Conference, HCI International 2015, Los Angeles, CA, USA, August 2-7, 2015, Proceedings, Part II* (pp. 608-617). Cham: Springer International Publishing.

González-Cutre, D., & Sicilia, Á. (2012). Motivation and Exercise Dependence. *Research Quarterly for Exercise and Sport, 83*(2), 318-329. doi:10.1080/02701367.2012.10599863

Groh, F. (2012). *Gamification: State of the art definition and utilization.* Paper presented at the 4th Seminar on Research Trends in Media Informatics, Institute of Media Informatics, Ulm University, Germany.

Gurman, T. A., Rubin, S. E., & Roess, A. A. (2012). Effectiveness of mHealth Behavior Change Communication Interventions in Developing Countries: A Systematic Review of the Literature. *Journal of health communication, 17*(sup1), 82-104. doi:10.1080/10810730.2011.649160

Haber, M. G., Cohen, J. L., Lucas, T., & Baltes, B. B. (2007). The relationship between self-reported received and perceived social support: A meta-analytic review. *American Journal of Community Psychology, 39*(1-2), 133-144.

Hagger, M. S., & Chatzisarantis, N. L. D. (2007). *Intrinsic motivation and self-determination in exercise and sport*. Champaign, IL, US: Human Kinetics.

Hair, J. F., Tatham, R. L., Anderson, R. E., & Black, W. (2006). *Multivariate data analysis* (Vol. 6). Upper Saddle River, NJ: Pearson Prentice Hall.

Halbesleben, J. R. (2006). Sources of social support and burnout: a meta-analytic test of the conservation of resources model. *Journal of applied psychology, 91*(5), 1134.

Hale, C. J., Hannum, J. W., & Espelage, D. L. (2005). Social support and physical health: The importance of belonging. *Journal of American College Health, 53*(6), 276-284.

Hamari, J. (2015). Do badges increase user activity? A field experiment on the effects of gamification. *Computers in Human Behavior*. doi:http://dx.doi.org/10.1016/j.chb.2015.03.036

Hamari, J., & Koivisto, J. (2013). *Social Motivations To Use Gamification: An Empirical Study Of Gamifying Exercise.* Paper presented at the Proceedings of the 21st European Conference on Information Systems (ECIS), Utrecht, The Netherlands.

Hamari, J., Koivisto, J., & Sarsa, H. (2014, 6-9 Jan. 2014). *Does Gamification Work? -- A Literature Review of Empirical Studies on Gamification.* Paper presented at the 47th International Conference on System Sciences, Hawaii.

Hanus, M. D., & Fox, J. (2015). Assessing the effects of gamification in the classroom: A longitudinal study on intrinsic motivation, social comparison, satisfaction, effort, and academic performance. *Computers & Education, 80*, 152-161. doi:http://dx.doi.org/10.1016/j.compedu.2014.08.019

Haskell, W., Lee, I., Pate, R., Powell, K., Blair, S., Franklin, B., . . . Bauman, A. (2007). Physical activity and public health: updated recommendation for adults from the American College of Sports Medicine and the American Heart Association. *Medicine and science in sports and exercise, 39*(8), 1423–1434.

Heinrichs, M., Baumgartner, T., Kirschbaum, C., & Ehlert, U. (2003). Social support and oxytocin interact to suppress cortisol and subjective responses to psychosocial stress. *Biological psychiatry, 54*(12), 1389-1398.

Hillery, G. (1982). *A research odyssey: Developing and testing a community theory*. London, UK: Transaction Publishers.

Hirsch, B. (1985). Adolescent coping and support across multiple social environments. *American Journal of Community Psychology, 13*(4), 381-392.

Hobbs, N., Godfrey, A., Lara, J., Errington, L., Meyer, T. D., Rochester, L., . . . Sniehotta, F. F. (2013). Are behavioral interventions effective in increasing physical activity at 12 to 36 months in adults aged 55 to 70 years? A systematic review and meta-analysis. *BMC medicine, 11*(1), 75. doi:doi:10.1186/1741-7015-11-75

Hsieh, Y. P. (2012). Online social networking skills: The social affordances approach to digital inequality. *First Monday, 17*(4).

Hsu, C.-L., & Lin, J. C.-C. (2008). Acceptance of blog usage: The roles of technology acceptance, social influence and knowledge sharing motivation. *Information & Management, 45*(1), 65-74. Retrieved from http://www.sciencedirect.com/science/article/pii/S0378720607001255

Hu, L. t., & Bentler, P. M. (1999). Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. *Structural Equation Modeling: A Multidisciplinary Journal, 6*(1), 1-55.

Hu, P. J.-H., Clark, T. H. K., & Ma, W. W. (2003). Examining technology acceptance by school teachers: a longitudinal study. *Information & Management, 41*(2), 227-241. doi:http://dx.doi.org/10.1016/S0378-7206(03)00050-8

Huberman, B. A., Romero, D. M., & Wu, F. (2008). Social networks that matter: Twitter under the microscope. *Available at SSRN 1313405*.

Hughes, D. J., Rowe, M., Batey, M., & Lee, A. (2012). A tale of two sites: Twitter vs. Facebook and the personality predictors of social media usage. *Computers in Human Behavior, 28*(2), 561-569. doi:http://dx.doi.org/10.1016/j.chb.2011.11.001

Hutchby, I. (2001). Technologies, texts and affordances. *Sociology, 35*(2), 441-456.

IDCresearch. (2016). Fitness Trackers in the Lead as Wearables Market Grows 3.1% in the Third Quarter, According to IDC Retrieved from http://www.idc.com/getdoc.jsp?containerId=prUS41996116

IDTechEx. (2015a). Key wearable technology markets. Retrieved from http://www.idtechex.com/research/articles/key-wearable-technology-markets-00008386.asp

IDTechEx. (2015b). Wearable Technology 2015-2025: Technologies, Markets, Forecast. Retrieved from http://www.idtechex.com/research/reports/wearable-technology-2015-2025-technologies-markets-forecasts-000427.asp

IHS. (2013). *Wearable Technology – Market Assessment*. Retrieved from London, UK: http://cdn2.hubspot.net/hub/396065/file-2568104498-pdf/Blog_Resources/IHS-Wearable-Technology.pdf?t=1427903372862

Ingledew, D., & Markland, D. (2008). The role of motives in exercise participation†. *Psychology and Health, 23*(7), 807-828.

Jankowski, N., & Van Selm, M. (2000). The promise and practice of public debate in cyberspace. In K. L. Hacker & J. van Dijk (Eds.), *Digital democracy: Issues of theory and practice* (pp. 149–165). London: Sage.

Jensen, K. B. (2010). *Media convergence: The three degrees of network, mass and interpersonal communication*: Routledge.

John, N. A. (2012). Sharing and Web 2.0: The emergence of a keyword. *New Media & Society*, 1461444812450684.

Joseph, R. P., Pekmezi, D. W., Lewis, T., Dutton, G. R., Turner, L. W., & Durant, N. H. (2013). Physical Activity and Social Cognitive Theory Outcomes of an Internet-Enhanced

Physical Activity Intervention for African American Female College Students. *Journal of Health Disparities Research and Practice, 6*(2), 1-18.

Kahn, E. B., Ramsey, L. T., Brownson, R. C., Heath, G. W., Howze, E. H., Powell, K. E., . . . Corso, P. (2002). The effectiveness of interventions to increase physical activity: A systematic review. *American journal of preventive medicine, 22*(4), 73-107.

Kankanhalli, A., Taher, M., Cavusoglu, H., & Kim, S. H. (2012). *Gamification: A new paradigm for online user engagement*. Paper presented at the International Conference on Information Systems (ICIS), Orlando, FL, USA.

Karanam, Y., Filko, L., Kaser, L., Alotaibi, H., Makhsoom, E., & Voida, S. (2014). *Motivational affordances and personality types in personal informatics*. Paper presented at the Proceedings of the 2014 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct Publication, Seattle, Washington.

Kas, K. (2014). *Nooit meer ziek*. Leuven: Koen Kas en Uitgeverij Van Halewyck.

Kassing, J. W., & Sanderson, J. (2010). Fan-athlete interaction and Twitter tweeting through the Giro: A case study. *International Journal of Sport Communication, 3*(1), 113-128.

Katz, M. L., & Shapiro, C. (1985). Network externalities, competition, and compatibility. *The American economic review, 75*(3), 424-440.

Kay, M., Santos, J., & Takane, M. (2011). *mHealth: New horizons for health through mobile technologies*. Retrieved from

Kietzmann, J. H., Hermkens, K., McCarthy, I. P., & Silvestre, B. S. (2011). Social media? Get serious! Understanding the functional building blocks of social media. *Business Horizons, 54*(3), 241-251.

Kilpatrick, M., Hebert, E., & Bartholomew, J. (2005). College Students' Motivation for Physical Activity: Differentiating Men's and Women's Motives for Sport Participation and Exercise. *Journal of American College Health, 54*(2), 87-94. doi:10.3200/JACH.54.2.87-94

King, A. C., & Frederiksen, L. W. (1984). Low-Cost Strategies for Increasing Exercise Behavior Relapse Preparation Training and Social Support. *Behavior Modification, 8*(1), 3-21.

Kline, R. (2016). *Principles and practice of structural equation modeling* (4th ed.). New York: Guilford publications.

Kock, N. (2004). The psychobiological model: Towards a new theory of computer-mediated communication based on Darwinian evolution. *Organization Science, 15*(3), 327-348.

Komito, L. (1998). The net as a foraging society: Flexible communities. *The information society, 14*(2), 97-106.

Koring, M., Richert, J., Lippke, S., Parschau, L., Reuter, T., & Schwarzer, R. (2012). Synergistic Effects of Planning and Self-Efficacy on Physical Activity. *Health Education & Behavior, 39*(2), 152-158. doi:10.1177/1090198111417621

Krishnamurthy, S. (2002). *E-commerce management: Text and cases*: South-Western Thomson Learning.

Krouse, R., Ransdell, L., Lucas, S., & Pritchard, M. (2011). Motivation, goal orientation, coaching, and training habits of women ultrarunners. *The Journal of Strength & Conditioning Research, 25*(10), 2835-2842.

LaChausse, R. (2006). Motives of Competitive and Non-Competitive Cyclists. *Journal of Sport Behavior, 29*(4), 304-314.

Lafferty, J. (2013). RunKeeper Leads The Pack With Facebook's Open Graph. Retrieved from http://www.adweek.com/socialtimes/runkeeper-developers-spotlight/412814

Lange, A., Van De Ven, J.-P., & Schrieken, B. (2003). Interapy: treatment of post-traumatic stress via the internet. *Cognitive Behaviour Therapy, 32*(3), 110-124.

LaRose, R., & Eastin, M. S. (2004). A social cognitive theory of Internet uses and gratifications: Toward a new model of media attendance. *Journal of Broadcasting & Electronic Media, 48*(3), 358-377. doi:http://dx.doi.org/10.1207/s15506878jobem4803_2

Lazar, A., Koehler, C., Tanenbaum, J., & Nguyen, D. H. (2015). *Why we use and abandon smart devices*. Paper presented at the Proceedings of the 2015 ACM International Joint Conference on Pervasive and Ubiquitous Computing, Osaka, Japan.

Lee, M.-C., & Tsai, T.-R. (2010). What Drives People to Continue to Play Online Games? An Extension of Technology Model and Theory of Planned Behavior. *International Journal of Human-Computer Interaction, 26*(6), 601-620. doi:10.1080/10447311003781318

Lewandowski, J., Rosenberg, B. D., Jordan Parks, M., & Siegel, J. T. (2011). The effect of informal social support: Face-to-face versus computer-mediated communication. *Computers in Human Behavior, 27*(5), 1806-1814. doi:http://dx.doi.org/10.1016/j.chb.2011.03.008

Li, F. (1999). The exercise motivation scale: Its multifaceted structure and construct validity. *Journal of Applied Sport Psychology, 11*(1), 97-115.

Lin, K., & Lu, H. (2011). Why people use social networking sites: An empirical study integrating network externalities and motivation theory. *Computers in Human Behavior, 27*(3), 1152-1161. doi:http://dx.doi.org/10.1016/j.chb.2010.12.009

Lin, N., Cook, K. S., & Burt, R. S. (2001). *Social capital: Theory and research*. New Brunswick, New Jersey: Transaction Publishers.

Lin, N., Simeone, R., Ensel, W., & Kuo, W. (1979). Social support, stressful life events, and illness: a model and an empirical test. *Journal of Health and Social Behavior, 20*(2), 108-119.

Lister, C., West, J. H., Cannon, B., Sax, T., & Brodegard, D. (2014). Just a Fad? Gamification in Health and Fitness Apps. *JMIR Serious Games, 2*(2), e9. doi:10.2196/games.3413

Locke, E., & Latham, G. (1994). Goal-setting theory. In J. B. Miner (Ed.), *Organizational Behavior 1: Essential Theories of Motivation and Leadership*. London: Routledge.

Lupton, D. (2013). Understanding The Human Machine [Commentary]. *Technology and Society Magazine, IEEE, 32*(4), 25-30.

Luszczynska, A., Sarkar, Y., & Knoll, N. (2007). Received social support, self-efficacy, and finding benefits in disease as predictors of physical functioning and adherence to antiretroviral therapy. *PATIENT EDUCATION AND COUNSELING, 66*(1), 37-42. doi:http://dx.doi.org/10.1016/j.pec.2006.10.002

Maher, C. A., Lewis, L. K., Ferrar, K., Marshall, S., De Bourdeaudhuij, I., & Vandelanotte, C. (2014). Are health behavior change interventions that use online social networks effective? A systematic review. *J Med Internet Res, 16*(2), e40. doi:10.2196/jmir.2952

Malik, S. H., Blake, H., & Suggs, L. S. (2014). A systematic review of workplace health promotion interventions for increasing physical activity. *British Journal of Health Psychology, 19*(1), 149-180.

Marett, K., & Joshi, K. (2009). The decision to share information and rumors: examining the role of motivation in an online discussion forum. *Communications of the Association for Information Systems, 24*(1), 47-68.

Markland, D., & Hardy, L. (1993). The Exercise Motivations Inventory: Preliminary development and validity of a measure of individuals' reasons for participation in regular physical exercise. *Personality and Individual Differences, 15*(3), 289-296.

Marwick, A., & Boyd, D. (2011). I tweet honestly, I tweet passionately: Twitter users, context collapse, and the imagined audience. *New Media & Society, 13*(1), 114-133.

Masters, K., Ogles, B., & Jolton, J. (1993). The development of an instrument to measure motivation for marathon running: the Motivations of Marathoners Scales (MOMS). *Research Quarterly for Exercise and Sport, 64*(2), 132-143.

Mateo, G. F., Granado-Font, E., Ferré-Grau, C., & Montaña-Carreras, X. (2015). Mobile phone apps to promote weight loss and increase physical activity: a systematic review and meta-analysis. *Journal of Medical Internet Research, 17*(11), e253.

McCann, J., & Bryson, D. (2009). *Smart clothes and wearable technology*. Cambridge, UK: Woolhead Publishing Limited.

McKay, H. G., King, D., Eakin, E. G., Seeley, J. R., & Glasgow, R. E. (2001). The Diabetes Network Internet-Based Physical Activity Intervention A randomized pilot study. *Diabetes Care, 24*(8), 1328-1334.

Mechant, P. (2012). An illustrated framework for the analysis of Web2. 0 interactivity. *Contemporary Social Science, 7*(3), 263-281.

Mekler, E. D., Br, F., #252, hlmann, Opwis, K., & Tuch, A. N. (2013). *Do points, levels and leaderboards harm intrinsic motivation?: an empirical analysis of common gamification elements*. Paper presented at the Proceedings of the First International Conference on Gameful Design, Research, and Applications, Toronto, Ontario, Canada.

Meyer, J. P., Becker, T. E., & Vandenberghe, C. (2004). Employee commitment and motivation: a conceptual analysis and integrative model. *Journal of applied psychology, 89*(6), 991.

Michie, S., Abraham, C., Whittington, C., McAteer, J., & Gupta, S. (2009). Effective techniques in healthy eating and physical activity interventions: A meta-regression. *Health Psychology, 28*(6), 690-701. doi:10.1037/a0016136

Michie, S., Ashford, S., Sniehotta, F. F., Dombrowski, S. U., Bishop, A., & French, D. P. (2011). A refined taxonomy of behaviour change techniques to help people change their physical activity and healthy eating behaviours: the CALO-RE taxonomy. *Psychology & Health, 26*(11), 1479-1498. doi:http://dx.doi.org/10.1080/08870446.2010.540664

Middelweerd, A., Mollee, J. S., van der Wal, C. N., Brug, J., & Te Velde, S. J. (2014). Apps to promote physical activity among adults: a review and content analysis. *Int J Behav Nutr Phys Act, 11*(1), 97. doi:10.1186/s12966-014-0097-9

Munson, S. A., & Consolvo, S. (2012, May 21–24). *Exploring goal-setting, rewards, self-monitoring, and sharing to motivate physical activity.* Paper presented at the 6th International Conference on Pervasive Computing Technologies for Healthcare (PervasiveHealth), San Diego, CA, USA.

Murcia, J. A. M., Román, M. L. d. S., Galindo, C. M., Alonso, N., & González-Cutre, D. (2008). Peers' Influence on Exercise Enjoyment: A Self-Determination Theory Approach. *Journal of sports science & medicine, 7*(1), 23-31. Retrieved from http://www.ncbi.nlm.nih.gov/pmc/articles/PMC3763348/

Must, A., Spadano, J., Coakley, E. H., Field, A. E., Colditz, G., & Dietz, W. H. (1999). The disease burden associated with overweight and obesity. *Jama, 282*(16), 1523-1529.

Nafus, D., & Sherman, J. (2014). Big data, big questions| this one does not go up to 11: the quantified self movement as an alternative big data practice. *International Journal of Communication, 8*, 11.

Newman, M. W., Lauterbach, D., Munson, S. A., Resnick, P., & Morris, M. E. (2011). *It's not that i don't have problems, i'm just not putting them on facebook: challenges and opportunities in using online social networks for health.* Paper presented at the Proceedings of the ACM 2011 conference on Computer supported cooperative work.

Norman, D. A. (1999). Affordance, conventions, and design. *interactions, 6*(3), 38-43.

Odongo, J., Makumbi, T., Kalungi, S., & Galukande, M. (2015). Patient delay factors in women presenting with breast cancer in a low income country. *BMC research notes, 8*(1), 1-6. doi:10.1186/s13104-015-1438-8

Ogles, B., & Masters, K. (2003). A typology of marathon runners based on cluster analysis of motivations. *Journal of Sport Behaviour, 26*(1), 69-85.

Ogles, B., Masters, K., & Richardson, S. (1995). Obligatory Running and Gender: A «An Analysis of Participative Motives and Training Habits. *Int. J. Sport Psychol, 26*, 233-248.

Orlikowski, W. J. (1992). The duality of technology: Rethinking the concept of technology in organizations. *Organization Science, 3*(3), 398-427.

Owen, N., Fotheringham, M., & Marcus, B. H. (2002). Communication technology and health behaviour change. In K. Glanz, B. K. Rimer, & F. M. Lewis (Eds.), *Health behaviour and health education: Theory, research and practice* (pp. 510-529). Hoboken, NJ: John Wiley & Sons.

Park, N., Kee, K. F., & Valenzuela, S. (2009). Being immersed in social networking environment: Facebook groups, uses and gratifications, and social outcomes. *CyberPsychology & Behavior, 12*(6), 729-733.

Parks, M. R. (2011). Social network sites as virtual communities. In Z. Papacharissi (Ed.), *A networked self: Identity, community, and culture on social network sites* (pp. 105-123). London, UK: Routlegde.

Patel, R., Chang, T., Greysen, S. R., & Chopra, V. (2015). Social Media Use in Chronic Disease: A Systematic Review and Novel Taxonomy. *Am J Med, 128*(12), 1335-1350. doi:10.1016/j.amjmed.2015.06.015

Pelletier, L., Fortier, M., Vallerand, R., Tuson, K., & et al. (1995). Toward a new measure of intrinsic motivation, extrinsic motivation, and amotivation in sports: The Sport Motivation Scale (SMS). *Journal of sport & exercise psychology, 17*(1), 35-53.

Porter, C. E. (2004). A Typology of Virtual Communities: A Multi-Disciplinary Foundation for Future Research. *Journal of Computer-Mediated Communication, 10*(1). doi:10.1111/j.1083-6101.2004.tb00228.x

Preacher, K. J., & Hayes, A. F. (2004). SPSS and SAS procedures for estimating indirect effects in simple mediation models. *Behavior research methods, instruments, & computers, 36*(4), 717-731. doi:http://dx.doi.org/10.3758/BF03206553

Price, M., Yuen, E. K., Goetter, E. M., Herbert, J. D., Forman, E. M., Acierno, R., & Ruggiero, K. J. (2014). mHealth: A Mechanism to Deliver More Accessible, More Effective Mental Health Care. *Clinical Psychology & Psychotherapy, 21*(5), 427-436. doi:10.1002/cpp.1855

Prochaska, J. J., Rodgers, M. W., & Sallis, J. F. (2002). Association of parent and peer support with adolescent physical activity. *Research Quarterly for Exercise and Sport, 73*(2), 206-210.

Prochaska, J., & Velicer, W. (1997). The transtheoretical model of health behavior change. *American journal of health promotion, 12*(1), 38-48.

Qiu, L., Lin, H., & Leung, A. K.-y. (2013). Cultural differences and switching of in-group sharing behavior between an American (Facebook) and a Chinese (Renren) social networking site. *Journal of Cross-Cultural Psychology, 44*(1), 106-121.

QRI. (2015). Consumer Trends: Towards a Healthy Lifestyle. Retrieved from http://www.qriconsulting.com/consumer-trends-towards-a-healthy-lifestyle/

Raebel, M. A., Malone, D. C., Conner, D. A., Xu, S., Porter, J. A., & Lanty, F. A. (2004). HEalth services use and health care costs of obese and nonobese individuals. *Archives of Internal Medicine, 164*(19), 2135-2140. doi:10.1001/archinte.164.19.2135

Ransdell, L. B., Taylor, A., Oakland, D., Schmidt, J., Moyer-Mileur, L., & Shultz, B. (2003). Daughters and mothers exercising together: effects of home-and community-based programs. *Medicine & science in sports & exercise, 35*(2), 286-296.

Reid, F. J., & Reid, D. J. (2010). The expressive and conversational affordances of mobile messaging. *Behaviour & Information Technology, 29*(1), 3-22.

Reyes Fernández, B., Montenegro Montenegro, E., Knoll, N., & Schwarzer, R. (2014). Self-efficacy, action control, and social support explain physical activity changes among Costa Rican older adults. *Journal of physical activity & health, 11*(8), 1573-1578. doi:10.1123/jpah.2013-0175

Rheingold, H. (1993). *The virtual community: Homesteading on the electronic frontier*. Reading, MA: Addison-Wesley Publishing Company.

Rogers, E. M. (1995). *Diffusion of Innovations* (4th ed.). New York: Free Press.

Rovniak, L., Anderson, E., Winett, R., & Stephens, R. (2002). Social cognitive determinants of physical activity in young adults: A prospective structural equation analysis. *Annals of Behavioral Medicine, 24*(2), 149-156. doi:10.1207/S15324796ABM2402_12

Ryan, R., & Deci, E. (2000a). Intrinsic and Extrinsic Motivations: Classic Definitions and New Directions. *Contemporary Educational Psychology, 25*(1), 54-67. doi:http://dx.doi.org/10.1006/ceps.1999.1020

Ryan, R., & Deci, E. (2000b). Self-determination theory and the facilitation of intrinsic motivation, social development, and well-being. *American psychologist, 55*(1), 68-78.

Ryan, R., Patrick, H., Deci, E., & Williams, G. (2008). Facilitating health behaviour change and its maintenance: Interventions based on self-determination theory. *European Health Psychologist, 10*(1), 2-5.

Sallis, J. F., Prochaska, J. J., & Taylor, W. C. (2000). A review of correlates of physical activity of children and adolescents. *Medicine and science in sports and exercise, 32*(5), 963-975.

Sawh, M. (2016). Fitness app buyouts: Why sports brands are spending big bucks. Retrieved from http://www.wareable.com/fitness-trackers/fitness-app-buyouts-has-anything-really-changed

Scheerder, J., & Vos, S. (2011). Social stratification in adults' sports participation from a time-trend perspective Results from a 40-year household study. *European Journal for Sport and Society, 8*(1-2), 31-44.

Scheidt, L. (2006). Adolescent diary weblogs and the unseen audience. In D. Buckingham & R. Willett (Eds.), *Digital generations: Children, young people, and new media*. London: Lawrence Erlbaum.

Schermelleh-Engel, K., Moosbrugger, H., & Müller, H. (2003). Evaluating the fit of structural equation models: Tests of significance and descriptive goodness-of-fit measures. *Methods of psychological research online, 8*(2), 23-74.

Schneider, H. (2016). *Self-knowledge through numbers and the operationalization of learning*. Paper presented at the Proceedings of the 2016 ACM International Joint Conference on Pervasive and Ubiquitous Computing: Adjunct, Heidelberg, Germany.

Schrock, A. R. (2015). *Communicative Affordances of Mobile Media: Portability, Availability, Locatability, and Multimediality* (Vol. 9).

Shi, L., Cristea, A. I., Hadzidedic, S., & Dervishalidovic, N. (2014). Contextual Gamification of Social Interaction – Towards Increasing Motivation in Social E-learning. In E. Popescu, R. W. H. Lau, K. Pata, H. Leung, & M. Laanpere (Eds.), *Advances in Web-Based Learning – ICWL 2014: 13th International Conference, Tallinn, Estonia, August 14-17, 2014. Proceedings* (pp. 116-122). Cham: Springer International Publishing.

Shilts, M. K., Horowitz, M., & Townsend, M. S. (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), 81-93. doi:doi:10.4278/0890-1171-19.2.81

Shuger, S. L., Barry, V. W., Sui, X., McClain, A., Hand, G. A., Wilcox, S., . . . Blair, S. N. (2011). Electronic feedback in a diet-and physical activity-based lifestyle intervention for weight loss: a randomized controlled trial. *International Journal of Behavioral Nutrition and Physical Activity, 8*(1), 1.

Silva, M. N., Markland, D., Minderico, C. S., Vieira, P. N., Castro, M. M., Coutinho, S. R., . . . Teixeira, P. J. (2008). A randomized controlled trial to evaluate self-determination theory for exercise adherence and weight control: rationale and intervention description. *BMC PUBLIC HEALTH, 8*(1), 1.

Simões, J., Redondo, R. D., & Vilas, A. F. (2013). A social gamification framework for a K-6 learning platform. *Computers in Human Behavior, 29*(2), 345-353. doi:http://dx.doi.org/10.1016/j.chb.2012.06.007

Slay, H. A., Hayaki, J., Napolitano, M. A., & Brownell, K. D. (1998). Motivations for running and eating attitudes in obligatory versus nonobligatory runners. *International Journal of Eating Disorders, 23*(3), 267-275.

Springer, A. E., Kelder, S. H., & Hoelscher, D. M. (2006). Social support, physical activity and sedentary behavior among 6(th)-grade girls: a cross-sectional study. *The International Journal of Behavioral Nutrition and Physical Activity, 3*, 8-8. doi:10.1186/1479-5868-3-8

Stragier, J., Evens, T., & Mechant, P. (2015). Broadcast yourself : an exploratory study of sharing physical activity on social networking sites. *MEDIA INTERNATIONAL AUSTRALIA, 155*, 120-129.

Stragier, J., & Mechant, P. (2014, May 21-24). *Social support for physical activity on social network sites : a content analysis.* Paper presented at the International Society for Behavioral Nutrition and Physical Activity, Annual meeting, Abstracts, San Diego, CA.

Stragier, J., Vanden Abeele, M., Mechant, P., & De Marez, L. (2016). Understanding persistence in the use of online fitness communities : comparing novice and experienced users. *Computers in Human Behavior, 64*(12), 34-42.

Straubhaar, J., LaRose, R., & Davenport, L. (2013). *Media now: Understanding media, culture, and technology*. Boston, Massachusetts, USA: Cengage Learning.

Strava - From the Beginning. (2012). Retrieved from https://cyclingtips.com/2012/02/strava-from-the-beginning/

Strava. (2016). Direct Messages on Strava. Retrieved from https://support.strava.com/hc/en-us/community/posts/208834887-Direct-Messages-on-Strava

Streiner, D. L., Norman, G. R., & Cairney, J. (2015). *Health measurement scales: a practical guide to their development and use* (5th ed.): Oxford University Press, USA.

Sundar, S. S., & Limperos, A. M. (2013). Uses and grats 2.0: New gratifications for new media. *Journal of Broadcasting & Electronic Media, 57*(4), 504-525.

Swan, M. (2012a). Health 2050: the realization of personalized medicine through crowdsourcing, the Quantified Self, and the participatory biocitizen. *Journal of Personalized Medicine, 2*(3), 93-118. doi:http://dx.doi.org/10.3390/jpm2030093

Swan, M. (2012b). Sensor mania! the internet of things, wearable computing, objective metrics, and the quantified self 2.0. *Journal of Sensor and Actuator Networks, 1*(3), 217-253. doi:http://dx.doi.org/10.3390/jsan1030217

Swan, M. (2013). The quantified self: Fundamental disruption in big data science and biological discovery. *Big Data, 1*(2), 85-99. doi:http://dx.doi.org/10.1089/big.2012.0002

Taiminen, H. (2016). How do online communities matter? Comparison between active and non-active participants in an online behavioral weight loss program. *Computers in Human Behavior, 63*, 787-795. doi:http://dx.doi.org/10.1016/j.chb.2016.06.002

Tervoort, R. (2016). Verbinden is het nieuwe sleutelwoord in de fitnessbranche. Retrieved from http://www.sportnext.nl/berichten/verbinden_is_het_nieuwe_sleutelwoord_in_de_fitnessbranche

Turner, J. W., Grube, J. A., & Meyers, J. (2001). Developing an optimal match within online communities: An exploration of CMC support communities and traditional support. *Journal of Communication, 51*(2), 231-251.

Uchino, B. N., Cacioppo, J. T., & Kiecolt-Glaser, J. K. (1996). The relationship between social support and physiological processes: a review with emphasis on underlying mechanisms and implications for health. *Psychological bulletin, 119*(3), 488-531.

Utter, J., Denny, S., Robinson, E. M., Ameratunga, S., & Watson, P. (2006). Perceived Access to Community Facilities, Social Motivation, and Physical Activity among New Zealand Youth. *Journal of Adolescent Health, 39*(5), 770-773. doi:http://dx.doi.org/10.1016/j.jadohealth.2006.04.009

Vallerand, R. J. (1997). Toward a hierarchical model of intrinsic and extrinsic motivation. *Advances in experimental social psychology, 29*, 271-360.

Van den Berg, M. H., Schoones, J. W., & Vlieland, T. P. V. (2007). Internet-based physical activity interventions: a systematic review of the literature. *Journal of Medical Internet Research, 9*(3), e26. doi:10.2196/jmir.9.3.e26

van der Bij, A. K., Laurant, M. G. H., & Wensing, M. (2002). Effectiveness of physical activity interventions for older adults: a review. *American journal of preventive medicine, 22*(2), 120-133. doi:http://dx.doi.org/10.1016/S0749-3797(01)00413-5

Van der Meulen, R., & Rivera, J. (2015). Gartner's 2015 Hype Cycle for Emerging Technologies Identifies the Computing Innovations That Organizations Should Monitor. Retrieved from http://www.gartner.com/newsroom/id/3114217

Van Dijk, J. (2006). *The Network Society: Social Aspects of New Media* (2nd ed.): Sage Publications Ltd.

Vandelanotte, C., & Maher, C. A. (2015). Why We Need More Than Just Randomized Controlled Trials to Establish the Effectiveness of Online Social Networks for Health Behavior Change. *Am J Health Promot, 30*(2), 74-76. doi:10.4278/ajhp.141204-CIT-605

Vanden Abeele, M., Schouten, A. P., & Antheunis, M. L. (2016). Personal, editable, and always accessible: An affordance approach to the relationship between adolescents' mobile messaging behavior and their friendship quality. *Journal of Social and Personal Relationships*. doi:10.1177/0265407516660636

Vanhaelewyn, B., Pauwels, G., De Wolf, P., Accou, T., & De Marez, L. (2015). *Digimeter: Measuring Digital Media Trends in Flanders* (8). Retrieved from Ghent, Belgium: https://www.iminds.be/nl/inzicht-in-digitale-technologie/digimeter/2015

Vanhaelewyn, B., Pauwels, G., De Wolf, P., Accou, T., & De Marez, L. (2016). *Digimeter: Measuring Digital Media Trends in Flanders* (8). Retrieved from Ghent, Belgium: https://www.iminds.be/nl/inzicht-in-digitale-technologie/digimeter/2016

A VC Lets a Bet Ride: the Story of Strava. (2013). Retrieved from http://www.pehub.com/2013/03/a-vc-lets-big-bet-ride

Venkatesh, V., Morris, M. G., Davis, G. B., & Davis, F. D. (2003). User acceptance of information technology: Toward a unified view. *MIS quarterly, 27*(3), 425-478.

Venkatesh, V., Thong, J. Y., & Xu, X. (2012). Consumer acceptance and use of information technology: extending the unified theory of acceptance and use of technology. *MIS Quarterly, 36*(1), 157-178.

Virnoche, M. E., & Marx, G. T. (1997). "Only Connect"—EM Forster in an Age of Electronic Communication: Computer-Mediated Association and Community Networks. *Sociological Inquiry, 67*(1), 85-100.

Vrasidas, C., & McIsaac, M. S. (2000). Principles of pedagogy and evaluation for web-based learning. *Educational Media International, 37*(2), 105-111.

Walther, J., & Boyd, S. (2002). Attraction to computer-mediated social support. In C. Lin & D. Atkin (Eds.), *Communication technology and society: Audience adoption and uses*. Cresskill, NJ Hampton Press.

Wang, Y., & Fesenmaier, D. R. (2003). Assessing motivation of contribution in online communities: An empirical investigation of an online travel community. *Electronic Markets, 13*(1), 33-45.

Wei, P.-S., & Lu, H.-P. (2014). Why do people play mobile social games? An examination of network externalities and of uses and gratifications. *Internet Research, 24*(3), 313-331. doi:10.1108/IntR-04-2013-0082

Wellman, B. (1998). The Privatization of Community: From Public Groups to Unbounded Networks. In J. Abu-Lughod (Ed.), *Millennial Milestone: A "Switching Crisis" in Sociology* (pp. 89-104). Barcelona: International Sociological Association.

Wellman, B. (2002). Little Boxes, Glocalization, and Networked Individualism. In M. Tanabe, P. van den Besselaar, & T. Ishida (Eds.), *Digital Cities II: Computational and Sociological Approaches: Second Kyoto Workshop on Digital Cities Kyoto,* *Japan, October 18–20, 2001 Revised Papers* (pp. 10-25). Berlin, Heidelberg: Springer

Wellman, B., Boase, J., & Chen, W. (2002). The networked nature of community: Online and offline. *It & Society, 1*(1), 151-165.

West, J. H., Hall, P. C., Hanson, C. L., Barnes, M. D., Giraud-Carrier, C., & Barrett, J. (2012). There's an app for that: Content analysis of paid health and fitness apps. *Journal of Medical Internet Research, 14*(3), e72.

West, L. (2015). Strava: challenge yourself to greater heights in physical activity/cycling and running. *British journal of sports medicine, 43*(19). doi:10.1136/bjsports-2015-094899

WHO. (2015). Global recommendations on physical activity for health. Retrieved from http://www.who.int/dietphysicalactivity/factsheet_recommendations/en/

Wicks, P., Massagli, M., Frost, J., Brownstein, C., Okun, S., Vaughan, T., . . . Heywood, J. (2010). Sharing health data for better outcomes on PatientsLikeMe. *Journal of Medical Internet Research, 12*(2), e19.

Williams, G., Hamm, M., Shulhan, J., Vandermeer, B., & Hartling, L. (2014). Social media interventions for diet and exercise behaviours: a systematic review and meta-analysis of randomised controlled trials. *BMJ Open, 4*(2), e003926.

Williams, G., Hamm, M. P., Shulhan, J., Vandermeer, B., & Hartling, L. (2014). Social media interventions for diet and exercise behaviours: a systematic review and meta-analysis of randomised controlled trials. *BMJ Open, 4*(2). doi:10.1136/bmjopen-2013-003926

Williams, S., & French, D. (2011). What are the most effective intervention techniques for changing physical activity self-efficacy and physical activity behaviour—and are they the same? *Health education research, 26*(2), 308-322.

Wing, R. R., & Jeffery, R. W. (1999). Benefits of recruiting participants with friends and increasing social support for weight loss and maintenance. *Journal of consulting and clinical psychology, 67*(1), 132-138.

Wininger, S. R. (2007). Self-determination theory and exercise behavior: An examination of the psychometric properties of the exercise motivation scale. *Journal of Applied Sport Psychology, 19*(4), 471-486.

Winzelberg, A. (1997). The analysis of an electronic support group for individuals with eating disorders. *Computers in Human Behavior, 13*(3), 393-407.

Winzelberg, A., Classen, C., Alpers, G., Roberts, H., Koopman, C., Adams, R., . . . Taylor, C. (2003). Evaluation of an internet support group for women with primary breast cancer. *Cancer, 97*(5), 1164-1173.

Wolf, G. (2011). What is The Quantified Self? Retrieved from http://quantifiedself.com/2011/03/what-is-the-quantified-self/

Woodruff, A., & Aoki, P. M. (2003). Media affordances of a mobile push-to-talk communication service. *arXiv preprint cs/0309001*.

Woods, V., & van der Meulen, R. (2016). Gartner Says Worldwide Wearable Devices Sales to Grow 18.4 Percent in 2016. Retrieved from http://www.gartner.com/newsroom/id/3198018

Yuan, S., Ma, W., Kanthawala, S., & Peng, W. (2015). Keep Using My Health Apps: Discover Users' Perception of Health and Fitness Apps with the UTAUT2 Model. *Telemedicine and e-Health, 21*(9), 735-741. doi:http://dx.doi.org/10.1089/tmj.2014.0148

Zhang, P. (2008). Technical opinion Motivational affordances: reasons for ICT design and use. *Communications of the ACM, 51*(11), 145-147.