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FULL PAPER

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 Studies in Communication and Media, 12. Jg., 1/2023, S. 92–113, DOI: 10.5771/2192-4007-2023-1-92

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More than counting steps: Identifying types of self-tracking usage among German young adults

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Abstract: Self-tracking technologies have been regarded both very optimistic and very critical. However, these conclusions are often based on single application studies and lack empirical evidence on actual self-tracking usage. We set out to identify types of self-tracking usage based on users' mobile media ensembles and their varying levels of engagement with the technology. Using latent class analysis, we empirically identified three types of self-tracking usage based on an online survey of a representative sample of N = 367 German self-trackers aged 18 to 30. Results indicate *interactive intensive self-trackers* spend more time physically active per week than *feedback-oriented basic self-trackers* and *purist step counters*. In addition, the injunctive norm-setting perception of algorithmic feedback is significantly higher for *feedback-oriented basic self-trackers* and *interactive intensive self-trackers* than *purist step counters*. Future research should be aware of these differences in young adults' engagement with self-tracking of physical activity and integrate them into empirical research, especially when aiming to assess the effects of self-tracking.

Keywords: Self-Tracking, physical activity, mobile media, wearables, usage.

Zusammenfassung: Mit der Nutzung von Self-Tracking-Technologien gehen sowohl sehr optimistische als auch sehr kritische Erwartungen einher. Diese beruhen jedoch zumeist auf Studien zu einzelnen Anwendungen. Umfassende empirische Erkenntnisse zur alltäglichen Nutzung von Self-Tracking-Technologien fehlen bisher. Ziel dieser Studie ist es daher, basierend auf dem alltäglichen Umgang mit der Technologie, Typen der alltäglichen Self-Tracking-Nutzung zu identifizieren. Mithilfe einer latenten Klassenanalyse (LCA) auf Basis einer Online-Befragung einer repräsentativen Stichprobe von N = 367 deutschen Self-Tracker*innen im Alter von 18 bis 30 Jahren haben wir drei Typen der Self-Tracking-Nutzung identifiziert: *Interactive Intensive Self-Trackers, Feedback-oriented Basic Self-Trackers* und *Purist Step Counters*. Die Ergebnisse zeigen, dass *Interactive Intensive Self-Trackers* mehr Zeit pro Woche mit körperlicher Aktivität verbringen als *Feedback-oriented Basic Self-Trackers* und *Purist Step Counters*. Außerdem ist die Wahrnehmung des algorithmischen Feedbacks der Self-Tracking-Technologie im Sinne einer injunktiven Norm bei *Feedback-oriented Basic Self-Trackers* und *Interactive Intensive Self-Trackers* signifikant stärker ausgeprägt als bei *Purist Step Counters*. Zukünftige Forschung sollte diese Unterschiede im Umgang junger Erwachsener mit Self-Tracking-Technologien zur

Erfassung körperlicher Aktivität berücksichtigen, insbesondere wenn es darum geht, die Effekte der Nutzung dieser Technologien zu bewerten.

Schlagwörter: Self-Tracking, körperliche Aktivität, mobile Medien, Wearables, Nutzung.

1. Introduction

Nowadays, most health-related apps, smartwatches, or wearables integrate self-tracking technogies (Reifegerste & Karnowski, 2020). And self-tracking physical parameters is a highly prevalent behavior in Germany. According to a recent study, 78 percent of German adults track some health parameters, and 42 percent use digital devices to do so (EPatient Analytics, 2022). In 2019, 24 percent of German adults used specific devices such as smartwatches or fitness trackers to monitor their physical activity (Splendid Research, 2019). Parameters monitored include step count, distance traveled, active time, or stairs climbed (Matthews et al., 2016).

With their increasing popularity among users worldwide, many health interventions use self-tracking technologies embedded in fitness apps, activity trackers, or smartwatches to enhance physical activity (Hermsen et al., 2016). And being physically active is one of the most crucial behaviors to prevent or manage chronic diseases and improving overall health and well-being (Sullivan & Lachman, 2017). So far, several studies have demonstrated that self-tracking technologies' features, such as self-monitoring, goal setting, and peer exchange, motivate users to be more active (Knittle et al., 2018; Wang et al., 2015).

Despite these encouraging results for health promotion through self-tracking, our knowledge of further (unintended) consequences of self-tracking physical activity is still minimal. Critics warn about the possible (non-intended) social effects of these technologies. They name norm activation, stigmatization, permanent optimization, illusions of control, and the ignorance of social determinants of health as possible risks, where responsibility is shifted to the individual (Lupton, 2013; Selke, 2016).

Both research strands, the optimistic healthcare studies, and the critical sociological perspective, yield either modest or mixed results (Schoeppe et al., 2016) or lack empirical testing. Based on the premise that self-tracking technology usage includes a very diverse set of activities (Lomborg & Frandsen, 2016), we argue that the ambivalent results might result from an oversimplification of self-tracking usage (i.e., the usage of self-tracking technologies), namely in effects studies. This oversimplification concerns the features within the app, digital technologies connected to the app, and, most importantly, varying levels of engagement with the technology (Wang et al., 2016). These diverse aspects lead to theoretically infinite nuance in self-tracking usage, going far beyond a mere dichotomy of use and non-use. As we will elaborate on below, Lomborg et al.'s (2018) conceptualization of three main aspects of self-tracking usage provides a valuable framework to take a more detailed look at the use of self-tracking technology, taking these nuances into account.

Consequently, our study aims to identify usage types of self-tracking technologies based on users' whole media ensembles rather than single device or app usage and their varying levels of engagement with the technology. Such a typology can serve as a solid basis for future empirical analyses of self-tracking technologies' positive or negative effects in healthcare or socialization research.

2. Theorizing self-tracking usage and its potential positive health outcomes

To untangle differences in the usage of self-tracking technologies, we make use of Lomborg et al.'s (2018) conceptualization of three main aspects of self-tracking usage: Based on different modes of engagement with self-tracking systems, they differentiate (1) registration, (2) algorithmic feedback, and (3) conversation. While *registration* only reports the logged data (e.g., the number of steps), the *algorithmic feedback* also provides advice based on the data collected (e.g., via messages). *Conversation* allows for data exchange and social comparison (e.g., with other app users). These different aspects can be related to different health-related effects:

Registration

Users rely on the basic feature of self-tracking systems for registration, where data is manually entered into the system or automatically monitored (Lomborg et al., 2018). Keeping a record of bodily measures can be pleasurable, whether or not the tracking is connected to a specific goal. This pleasure originates from feelings of gaining control, self-efficacy, and competence because users have archived their data for future reference and insights (Lomborg et al., 2018). It also increases users' self-awareness and mindfulness about their behavior. In addition, Hermsen et al. (2016) point out that digital technologies can make visible specific otherwise unrecognized parameters (e.g., habitual behavior). Hence, accurate self-monitoring (i.e., a low discrepancy between self-reported and actual performance) significantly improves (Kim et al., 2013).

These positive associations with registration might also explain why it is widely used (also independent of digital devices) as a psychological intervention technique at the first stage of self-regulation and behavior change (Stiglbauer et al., 2019) based on control theory and self-determination theory. Thus, simple self-monitoring activities can positively affect health-related outcomes, like increased intentions for physical activity (Knittle et al., 2018), users' perceived physical health, and a sense of accomplishment (Stiglbauer et al., 2019).

Algorithmic Feedback

Once the data are collected, most self-tracking technologies also provide their analysis, interpretation, and representation. This algorithmic feedback can be provided in statistics, visualizations, or explicit messages (Lupton, 2016a). This advice or recommendations are mainly based on goals (e.g., 10,000 steps a day) that are either set by the system (default values) or the user. In contrast to mere data collection, this communication with the system entails comparing users' physical performance to another value, either their past behavior (historical comparison) or the set norms or goals (normative comparison) (Hermsen et al., 2016).

According to social cognitive theory (Bandura, 2005) and social norms theory (Rimal, 2008), individuals compare monitored values with goals. As fostered by algorithmic feedback, the perception of deviation might initiate health-related behavioral changes (Stiglbauer et al., 2019). Like self-monitoring per se, the setting and evaluation of goals are established psychological intervention techniques that stimulate intention formation and behavior change (Knittle et al., 2018). Thus, feedback from external sources can play an important role in disrupting habitual behavior and initiating health-related behavior change, such as increased physical activity (Hermsen et al., 2016).

Conversation

Conversation constitutes the third aspect of self-tracking. It allows for data exchange and social comparison with other users (Lomborg et al., 2018). These conversations can occur within the app, on social media, or face-to-face, although the latter is often neglected in intervention studies (Hermsen et al., 2016). In addition, users might also discuss tracking experiences with others, provide information about the technologies, or support coping with barriers to using the technology (Lomborg et al., 2018).

Overall, the evidence on the effects of peer support and social influence on health promotion interventions is mixed. Knittle et al. (2018) found no significant associations between social influences and motivational outcomes in their systematic review of various health interventions targeting physical activity. However, addressing descriptive norms (i.e., comparative information about the behavior of others) in health messages can increase physical activity (Priebe & Spink, 2012). Still, the current empirical evidence remains inconclusive as most studies focusing on (standalone) app interventions do not differentiate the effects of different conversational aspects of the intervention or do not measure the impact of the social influence component. Hence, despite most app interventions incorporating peer support or team challenges, these social elements' effect on the interventions cannot be deducted from existing studies (Schoeppe et al., 2016).

Hence, to provide a better basis for future assessments of effects and given the established differentiation of self-tracking modes by Lomborg et al. (2018), we first ask:

> *RQ1: To what extent do users engage in registration, algorithmic feedback, and conversation when using self-tracking technologies to track their physical activity?*

As described above, these three aspects are not mutually exclusive but can enhance each other (Lomborg et al., 2018). Therefore, to unveil users' individual self-tracking practices, we must look at the assemblages of these three aspects. Consequently, we also ask:

> *RQ2: Based on users' engagement in registration, algorithmic feedback, and conversation, which types of self-tracking usage can be identified?*

Thirdly, given the above-discussed inconclusive current empirical evidence on the potential of registration, algorithmic feedback, and conversation to promote physical activity, we also ask:

> *RQ3: How do users engaging in different types of self-tracking usage (see RQ2) differ with regard to their physical activity levels?*

Media ensembles for self-tracking practices

In addition to identifying usage styles based on users' engagement with technology, we must consider the technologies' characteristics. Many studies combine very different technological elements within one app intervention, ignoring that different characteristics can have very different effects (Wang et al., 2016). However, most self-tracking practices involve devices that can be described as metamedia, i.e., structures into which an unlimited number of constituent media can be nested through individual configuration and programming (Humphreys et al., 2018). The metamedium does not pre-set the combinations of constituent media nested in it. Instead, users can individually configure and program their sets of constituent media. No two smartphones look alike, but each user configures them to their personal needs, resulting in individual and variable sets of apps installed on the smartphone. This variability poses a challenge to the modeling of self-tracking usage styles. However, existing evaluations are often limited to standalone app interventions, although multi-component interventions appear more efficacious (Schoeppe et al., 2016).

In addition, as different authors (Lomborg & Frandsen, 2016; Lupton, 2016a) point out, to study self-tracking, it is also essential to focus on the apps in use on one device and the media ensemble, potentially including several supplementary devices. For registration, users might not only use the app on the smartphone that provides self-tracking features. They might also use sensors they carry or wear on their bodies (e.g., wearables or smart clothing) to track physical activity (Lupton, 2016a). While dedicated self-trackers might use multiple devices and sensors, more casual users might confine themselves to a limited number of these possibilities (Lomborg et al., 2018). Thus, going beyond identifying the self-tracking usage styles described above, we need to compare these based on the technologies involved (Lomborg et al., 2018).

> *RQ4: How do the identified types of self-tracking usage differ regarding the technologies involved?*

Considering the potential harms of self-tracking practices

Although information about the self – as provided by self-tracking technologies – might be perceived as valuable and practical (Sharon & Zandbergen, 2017), it could nonetheless have non-intended consequences on users' formation of social perceptions. Such consequences could be illusions of (objective) control, the reduction of bodily phenomena to quantifiable parameters, and the ignorance of social determinants of health (Lupton, 2016b; Selke, 2016). Critics like Morozov (2013) or van Dijck (2014) fear that individuals' perception of their bodies and trust in subjective and intuitive knowledge decreases. At the same time, they only monitor their bodies via technology and follow an ideology of dataism (Van Dijck, 2014). These risks are especially relevant in young adulthood, a phase of substantial transformations pertinent to developing (body) identity and health behavior (Böhnisch & Lenz, 2015). However, there is only little empirical evidence on such non-intended potentially harmful effects of *registration* of physical activity parameters on body perception, health identity, and personal mindfulness so far (Simpson & Mazzeo, 2017).

Algorithmic feedback might not only have health-promoting effects but can also lead to annoyance and discouragement when users fail to reach set goals (Lazar et al., 2015). Based on reactance theory, we can assume that users are motivated to counter when they perceive a threat to their freedom of action (Brehm, 1966). Furthermore, algorithms process data based on standards and set values to evaluate the tracked data to provide this feedback to users. However, e.g., due to competitive advantages, app producers often do not reveal information about the algorithms or the source of their standards (Meidert et al., 2018; Reifegerste & Karnowski, 2020). One famous example of such questionable standards is the goal of "10,000 steps a day", which is not based on any scientific health advice, but instead had its origins in the promotional materials of a Japanese step counter-producer (Lee et al., 2019). In addition, critical sociologists argue that users might perceive the algorithmic feedback in digital self-tracking as a form of surveillance, leading to mistrust, reactance, and loss of privacy (Lomborg & Frandsen, 2016). Thus, different elements of algorithmic feedback could be harmful to users' self-perceptions.

In contrast, Sharon and Zandbergen (2017) conclude that self-tracking could also be a means of resistance to dominant social norms and conventions because users can actively engage with their data. This engagement might empower them against the tracking done by a physician or other medical staff (Sharon & Zandbergen, 2017). To investigate these opposing views, we therefore ask:

RQ5: How do the identified types of self-tracking usage differ regarding

(a) users' engagement with algorithmic feedback?

(b) users' reactance towards algorithmic feedback?

Whether or not they increase or decrease users' autonomy, the algorithmic feedback embedded in self-tracking technologies may serve as guides, advice-givers, or autonomous agents with potential persuasive power. Thus, they can be conceptualized as social agents exerting a particular socialization function in users' health socialization. Based on our general knowledge of norms as essential determinants of health-related behaviors (Geber et al., 2016) – it finally seems worthwhile to assess whether users perceive these messages as injunctive norms. Injunctive norms are users' perceptions of the approval of their actions by others which have previously proven to be influential on health behaviors (Rimal & Real, 2005). We now ask whether algorithms as well can be perceived as such others, providing injunctive norms. Thus, the final research question explores the following:

> *RQ6: How do the identified types of self-tracking usage differ regarding the perception of injunctive norms embedded in algorithmic feedback?*

3. Method

To answer these questions, we conducted a cross-sectional online survey among German young adults (18 to 30 years) using mobile technologies to track their physical activity in May 2019. Participants had to own a smartphone and use self-tracking apps. There were no limitations regarding the use of specific apps or the use or non-use of connected wearables. Before starting the study, respondents provided their informed consent. Only the measures reported in this article were gathered in this study. No personal information was collected. Before fielding the survey, the questionnaire was pretested for comprehensibility and technical functionality.

We focused on young adults aged 18 to 30 for two reasons. First, this age group is much more likely to use digital devices for self-tracking physical parameters than traditional ways such as paper-and-pencil notes (EPatient Analytics, 2022). Second, this phase of early adulthood is a critical time for establishing long-term health behavior patterns influencing future health (behaviors) (Nelson et al., 2008; Sawyer et al., 2012).

Participants

The recruitment of our quota sample was conducted by the German online-access panel provider respondi and yielded 538 completed interviews. The panel provider respondi incentivized respondents. We excluded 171 interviews because of a failure to meet the quality criteria. Examples for exclusion include too quick or too slow responses, unintelligible answers to knowledge questions (Leiner, 2019), or missing values for core constructs. Thus, the final sample comprises 367 participants aged 18 to 30 (M = 23.7, SD = 4.0). With 56.9 percent of respondents being female and 13.4 percent low, 29.2 percent middle, and 57.5 percent high educational levels, this sample roughly represents the German population in this age range (Statista, 2017).

Measures

We developed the measure of modes of engagement with self-tracking systems based on the framework provided by Lomborg et al. (2018). *Registration* was assessed by asking participants which parameters they tracked with their preferred self-tracking app, either automatically or manually, and on which devices they viewed the parameters tracked. We measured *algorithmic feedback* by asking which types of algorithmic feedback users got when self-tracking, differentiating general advice (e.g., “You should walk 10,000 steps a day” or “You shouldn’t sit for too long at a stretch.”), visualized feedback (e.g., a progress bar that is filled for 10,000 steps or a ring that closes for 10,000 steps), and personalized advice (e.g., “You’ve already walked 7,000 steps today. Go for a walk to make it to 10,000!”). *Conversation* was measured by the frequency of users discussing their self-tracking usage within the app, on social media, or in interpersonal discussions.

We measured physical activity in two different ways based on a representative study on the health of adults (Krug et al., 2013). First, we assessed the weekly minutes of physical activity using the suggested method. Second, self-perception to be physically active was measured using three items. The technology used for self-tracking was assessed by asking participants which smartphone and wearable they used and which app they used most often for self-tracking. To gauge users’ engagement with the algorithmic feedback, we asked users whether they were able to change the goals embedded in the algorithmic feedback (*ability to change goals*) and how often they did so (*frequency of changing goals*) (for all reliability coefficients, see table 1). Reactance towards these messages was measured using three items based on the scales by Herzberg (2002).

Table 1. Parameters of indices

	Number of items	*M*	*SD*	Cronbach‘s Alpha
Self-perception to be physically active	6	3.60	0.84	.87
Reactance toward algorithmic feedback	3	1.97	0.99	.84
Injunctive norm algorithmic feedback	4	3.82	0.87	.81

The perceived injunctive norms inherent in algorithmic feedback were measured based on the scales by Rimal and Real (2005). Both scales are measured using 5-point Likert scales. Finally, we asked for respondents’ demographic characteristics, *gender*, *age, educational level, income, and occupation.* The entire questionnaire can be viewed here: https://osf.io/r7y6m/?view_only=fba921ee9cec49d9bb5c277853efa0f3.

4. Results

Concerning the first research question, young adults use self-tracking technologies across all three modes of engagement with self-tracking systems (see table 2).

Table 2. Modes of engagement with self-tracking systems

	n	(%)
Registration	366	99.7
Algorithmic feedback	306	83.4
General feedback	201	54.8
Visualized results	195	53.1
Personalized feedback	137	37.3
Rewards	171	46.6
Conversation	303	82.6
within the app	154	42.0
in social media	98	26.7
in interpersonal talks	291	79.3

Registration, i.e., the mere recording of physical activity, is not surprisingly used by (nearly) all participants. Most participants (83.4%) get algorithmic feedback from their devices, albeit with some variance concerning the types of feedback provided. General advice and visualized results are the most common types of feedback, whereas only about one-third report getting personalized feedback (see table 2). Finally, the data tracked by self-tracking technologies is also a source for conversations, with 82.6 percent of our participants engaging in discussions with others based on their self-tracking. Despite the possibilities offered by these technologies, interpersonal follow-up communication still is the dominant way to discuss self-tracked parameters.

We used the clustering technique of latent class analysis (LCA) to answer our second research question. Latent class analysis has various advantages over traditional cluster analysis. It allows for the classification of variables at each measurement level, and different measurement levels can be integrated into the analysis. In contrast to traditional cluster analysis, LCA does not necessarily result in a cluster solution, and it can also reject the clustering of the data (Fraley & Raftery, 1998). Latent class analysis provides statistical tests to identify the exact number of clusters. Accordingly, it is less arbitrary than traditional cluster analysis. Because of its probabilistic conception, LCA also considers the possibility that the clustered variables might not be wholly reliable or completely valid (Karnowski, 2017).

We conducted our latent class analysis using the R package *poLCA (v. 1.4.1*, Linzer & Lewis, 2011), clustering all aspects of modes of engagement with self-tracking systems, i.e., registration, algorithmic feedback, and conversation. We first ran the one- to ten-class solutions, with the three-class solution yielding the best model fit based on the Bayesian Information Criterion (BIC, see table 3). This model generates a satisfactory entropy of .86 (Celeux & Soromenho, 1996). We identified three types of self-tracking usage: *interactive intensive self-trackers*, *feedback-oriented basic self-trackers*, and *purist step counters*.

Table 3. Model fit 1- to 10-cluster-solutions

Model	Number of classes	df	BIC
Model 1	1	327	10857.2
Model 2	2	287	10414.9
Model 3	**3**	**247**	**10377.9**
Model 4	4	207	10379.8
Model 5	5	167	10437.1
Model 6	6	127	10532.1
Model 7	7	87	10694.2
Model 8	8	47	10845.7
Model 9	9	7	11027.0
Model 10	10	-33	11181.8

The *interactive intensive self-trackers* are the smallest group in our sample. These users are most likely to track nearly all parameters automatically. Hence, these users show the most intense self-tracking usage regarding parameters tracked. Like both other clusters, *interactive intensive self-trackers* are most likely to view their parameters tracked on their smartphones. Compared to the *feedback-oriented basic self-trackers* and the *purist step counters*, they are also most likely to view parameters tracked on a smartwatch. *Interactive intensive self-trackers* are also likely to talk about their self-tracking routines within the app, on social media, or in personal conversations. Algorithmic feedback is part of their self-tracking usage, but overall a little less likely than among the *feedback-oriented basic self-trackers*.

Table 4. 3-Cluster solution: Conditional item response probabilities

	Interactive intensive self-trackers	Feedback-oriented basic self-trackers	Purist step counters
Relative cluster size	23.0%	44.0%	33.1%
Registration: Parameters tracked			
Heart rate			
automatically	77.7%	52.3%	8.8%
manually	8.6%	12.1%	1.2%
don’t know	1.2%	0.0%	15.5%
Height meter/Floors			
automatically	68.4%	50.6%	35.2%
manually	12.7%	1.5%	0.0%
don’t know	8.1%	7.3%	17.6%
Distance traveled			
automatically	87.8%	98.6%	69.2%
manually	8.5%	0.6%	1.6%
don’t know	0.0%	0.0%	4.9%
Calories burned			
automatically	70.2%	70.9%	32.6%
manually	20.9%	7.5%	12.0%
don’t know	5.6%	1.5%	12.2%

	Interactive intensive self-trackers	Feedback-oriented basic self-trackers	Purist step counters
Step count			
automatically	86.0%	96.0%	89.4%
manually	7.3%	0.6%	0.0%
don't know	0.0%	1.3%	1.6%
Duration physical activity			
automatically	81.5%	88.5%	34.6%
manually	13.6%	6.9%	12.0%
don't know	3.5%	2.0%	19.5%
Velocity			
automatically	73.9%	53.0%	16.9%
manually	17.5%	2.2%	0.0%
don't know	6.8%	8.9%	22.9%
Registration: Viewing			
On smartphone (pull)	86.9%	86.7%	85.5%
On smartphone (push)	36.1%	36.8%	22.8%
On smartwatch	30.3%	24.1%	5.1%
On fitness tracker	5.5%	22.7%	1.7%
Algorithmic feedback			
General suggestions	68.1%	70.4%	25.0%
Graphic display of parameters tracked	61.3%	71.5%	24.1%
Personalized notes to reach a certain goal	50.3%	50.1%	11.3%
Awards for achievements	51.9%	66.7%	17.0%
No feedback	4.2%	0.0%	46.9%
Conversation			
In app			
at least weekly	7.8%	5.4%	2.3%
at least monthly	73.8%	12.6%	11.1%
less often	17.1%	9.8%	9.1%
never	1.3%	72.2%	77.5%
In social media			
at least weekly	21.8%	1.3%	0.7%
at least monthly	42.0%	1.3%	1.8%
less often	19.9%	6.1%	8.8%
never	16.3%	91.4%	88.7%
In personal conversation			
at least weekly	16.3%	22.8%	20.3%
at least monthly	77.1%	31.9%	27.7%
less often	5.8%	21.7%	21.5%
never	0.9%	23.6%	30.4%

The second type of self-tracking usage can be described as *feedback-oriented basic self-trackers*. This usage type likely includes automatic tracking of distances traveled, step count, and the duration of physical activity (for all conditional item response probabilities, see table 4). Additional parameters like heart rate, height meters, calories burned, or velocity might get automatically tracked, but not necessarily. Despite the low probability (12.1%), this cluster's likelihood of manually tracking the heart rate is the highest. Like all respondents, *feedback-oriented basic self-trackers* are most likely to view their parameters tracked on the smartphone. In addition, these users are most likely to view their parameters on a fitness tracker. Regarding conversation, they are relatively unlikely to talk about their self-tracking usage on social media and within their fitness apps. Still, they will sometimes do so in personal conversations. Algorithmic feedback is essential to the *feedback-oriented basic self-trackers'* self-tracking usage. They are most likely among all user types to receive algorithmic feedback, with general suggestions and graphic displays of parameters tracked being the most likely. With a relative cluster size of 44.0 percent, the most significant part of our respondents belongs to this type.

Compared to *feedback-oriented self-trackers* and *interactive intensive self-trackers, purist step counters* engage in less intensive self-tracking usage. They are most likely only to track step count and distance traveled. These users will probably only view their parameters tracked on their smartphones. *Purist step counters* are unlikely to engage in conversations about their self-tracking usage in social media or apps, but they will sometimes discuss these in personal conversations. Algorithmic feedback is not necessarily part of these self-tracking practices, with the highest probability of getting no algorithmic feedback. The relative cluster size of *purist step counters* is 33.1 percent.

Next, we will compare users of our three types of self-tracking usage regarding their physical activity (RQ 3). For these ANOVAs and the following analyses answering RQs 4 to 6, we assigned participants to the type of self-tracking usage they most probably belong to. Regarding physical activity, we see that levels are highest among *interactive intensive self-trackers*, considering a measure of minutes of intensive physical activity per week and the self-perception of being physically active (see table 5).

Table 5. Types of self-tracking by physical activity

	Interactive intensive self-trackers	Feedback-oriented basic self-trackers	Purist step counters	*F*-value	*P*	$\eta2$
Minutes of physical activity per week	157.0_b	116.3_a	131.7_{ab}	4.72	.010	.03
Self-perception to be physically active	4.0_b	3.5_a	3.5_a	11.29	<.001	.06

Note. Means with different subscripts differ at the p = .05 level by Tukey's HSD

As discussed above, the technology used for self-tracking physical activity constrains and enables specific uses while, simultaneously, usage behaviors shape users' technological setup. Hence, we will now compare the three types of self-tracking usage by the technologies involved (RQ 4, see table 6). Overall, most users in our sample use Android smartphones (66.9%), mirroring Android's overall market share of about 80 percent in Germany (Kantar, 2019). Comparing the self-tracking types, the number of Android users is highest among feedback-oriented basic self-trackers and lowest among *purist step counters*. There are apparent differences between the groups regarding wearables: nearly two-thirds (61.9%) of *interactive intensive self-trackers* use a smartwatch, and about a third of *feedback-oriented basic self-trackers* (30.4%) do so. Usage of fitness trackers is lower among both groups, with around a quarter of both *feedback-oriented basic self-trackers* (28.0%) and *interactive intensive self-trackers* (22.6%) using such a device. Among *purist step counters,* usage of both types of wearables is very scarce. *Feedback-oriented basic self-trackers* often use the app Samsung Health, reflecting the high number of Android users in this cluster. But quite a large number of users in this cluster will also use many other apps. *Interactive intensive self-trackers* most often use either Samsung Health or Apple Health. *Purist step counters'* app use is mainly scattered among an extensive selection of different tracking apps, but Apple Health still yields the highest share.

Table 6. Types of self-tracking by smartphone OS, wearable, and most used app for self-tracking

	Interactive intensive self-trackers	Feedback-oriented basic self-trackers	Purist step counters	Total	$\chi 2$	*P*
Smartphone OS						
Android	65.5%	74.5%	57.9%	66.9%	8.79	.012
iOS	34.5%	25.5%	42.1%	51.3%		
Smartwatch	61.9%	30.4%	6.6%	29.8%	72.55	<.001
Fitness tracker	22.6%	28.0%	6.6%	19.7%	20.51	<.001
Most used app						
Apple Health	26.2%	18.6%	28.1%	23.5%	25.24	.001
Fitbit	11.9%	12.4%	4.1%	9.6%		
Google-Fit-App	11.9%	8.7%	6.6%	8.7%		
Samsung Health	27.4%	32.9%	17.4%	26.5%		
Other	22.6%	27.3%	43.8%	31.7%		

Algorithmic feedback is one core component of self-tracking technologies. Hence, we will analyze how far self-tracking usage types differ regarding users' engagement with the algorithmic feedback (RQ 5a). More than three-quarters of *feedback-oriented basic self-trackers* and *interactive intensive self-trackers* can change the goals on which their algorithmic feedback is based. In contrast, nearly two-thirds of *purist step counters* do not have any goals set (see table 7). Accordingly, this type's engagement with goalsetting is also the lowest. Most users in this cluster, who have goals set, never change these. Interestingly, engagement with the goals set is lower for *feedback-oriented basic self-trackers* than *interactive intensive self-trackers*, despite *feedback-oriented self-trackers'* overall orientation towards algorithmic feedback. Nearly half of the latter change their goals at least monthly, whereas 89.5 percent of *interactive self-trackers* do so less than monthly or never (see table 7).

Table 7. Types of self-tracking by the ability to and frequency of changing goals on which algorithmic feedback is based

	Interactive intensive self-trackers	Feedback-oriented basic self-trackers	Purist step counters	Total	$\eta 2$	P
Ability to change goals in algorithmic feedback						
No, or do not know	2.4%	11.8%	12.4%	9.8%		
Yes	83.3%	80.7%	24.8%	62.8%	132.14	<.001
No goals set	14.3%	7.5%	62.8%	27.3%		
Frequency of changing goals in algorithmic feedback						
at least monthly	41.7%	10.6%	3.3%	15.3%		
less often	32.1%	52.2%	14.0%	35.0%	121.62	<.001
never	26.2%	37.3%	82.6%	49.7%		

In addition to their engagement with the goals on which the algorithmic feedback is based, users might also feel differently towards the messages conveyed in algorithmic feedback. Reactance towards the embedded messages is overall relatively low (RQ5b). Notably, the reactance level is considerably higher among *interactive, intensive users*, fitting in with their intensive engagement with goal setting and a higher tendency to engage in discussions of their self-tracking usage (see table 8).

Table 8. Types of self-tracking by reactance towards algorithmic feedback

	Interactive intensive self-trackers	Feedback-oriented basic self-trackers	Purist step counters	F-value	P	$\eta 2$
Reactance toward algorithmic feedback	2.6_b	1.7_a	1.9_a	25.52	<.001	.14

Notes. Means with different subscripts differ at the p = .05 level by Tukey's HSD
Scale 1 "do not agree at all" to 5 "totally agree."

Finally, the algorithmic feedback embedded in users' self-tracking styles does convey injunctive norms. Hence, in the last step, we will assess differences in users' perceptions of the norm-setting capacities of algorithmic feedback embedded in self-tracking (RQ 6). The injunctive norm-setting perception of algorithmic feedback is significantly higher for *feedback-oriented basic self-trackers* and *interactive intensive self-trackers* than *purist step counters* (see table 9).

Table 9. Types of self-tracking by perceived social norms

	Interactive intensive self-trackers	Feedback-oriented basic self-trackers	Purist step counters	*F*-value	*P*	$\eta 2$
Injunctive norm algorithmic feedback	4.1_a	3.9_a	3.5_b	11.77	<.001	.06

Notes. Means with different subscripts differ at the $p = .05$ level by Tukey's HSD
Scale 1 "do not agree at all" to 5 "totally agree."

5. Discussion

We set out to identify usage types of self-tracking technologies based on users' whole media ensembles and their varying levels of engagement with the technology. We built upon Lomborg et al.'s (2018) conceptualization of different modes of engagement: registration, algorithmic feedback, and conversation. Surveying a sample of German young adults engaging in self-tracking, we found that they all engage in some form of registration. About 80 percent respectively engage in some form of algorithmic feedback or conversation. Going beyond this first glimpse into young adults' self-tracking usage, we condensed their engagement in these three modes of engagement into three types of self-tracking usage based on latent class analysis. While most self-trackers can be described as *feedback-oriented basic self-trackers,* we also found *purist step counters* and *interactive intensive self-trackers*.

Interactive intensive self-trackers show the most intense self-tracking usage regarding parameters tracked. Most *interactive intensive self-trackers* rely on a smartwatch and its specific affordances to support their self-tracking practices. Along with their intensive engagement with different modes of self-tracking, the level of physical activity is also highest among users in this cluster. Algorithmic feedback is integral to their self-tracking usage, but overall, it is less likely than among the *feedback-oriented basic self-trackers*. Still, *interactive intensive self-trackers* strongly engage with this algorithmic feedback, adjusting goals more often than other users. Accordingly, they also show the highest reactance towards algorithmic feedback and perceive it to set injunctive norms. *Interactive intensive self-trackers* are also very likely to talk about their self-tracking routines within the app, on social media, or in personal conversations. Hence, especially among these users, we can expect positive outcomes attributed to self-tracking: Firstly, a stimulating effect on physical activity enhanced through peer support and high empowerment seem most likely for these users. In addition, going along with their emancipated dealing with the technology, reflected in both their high engagement with and higher reactance towards algorithmic feedback (in comparison to other users), we can expect higher autonomy and empowerment (Schmietow & Marckmann, 2019) and the development of a certain self-expertise as conceptualized by Heyen (2020).

Feedback-oriented basic self-trackers also automatically track various health parameters, but not as extensively as the *interactive intensive self-trackers*. They are most likely among all user types to receive algorithmic feedback, with general suggestions and graphic displays of parameters tracked being the most likely.

Contrary to the *interactive intensive self-trackers*, they adjust the goals less. Instead, they rely on pre-sets, which they also perceive to set injunctive norms. Conversation is also less prevalent in their usage styles compared to the *interactive intensive self-trackers*. But still, they will sometimes do so in personal conversations. Given these usage styles, these users seem most vulnerable to some of the negative consequences of self-tracking imagined by several critical scholars. Although their reliance on algorithmic feedback and its norm-setting capacity might induce positive change (Stiglbauer et al., 2019), their dependence on pre-set goals leaves them with tremendous yet untapped potential to take charge of their physical activity goals. At the same time, this reliance on algorithmic feedback might also lead to adverse effects such as illusions of (objective) control, the reduction of bodily phenomena to quantifiable parameters, and the ignorance of social determinants of health (Lupton, 2016b; Selke, 2016). Therefore, future longitudinal studies should investigate the interrelations between this type of self-tracking usage and positive and negative effects on physical activity and well-being.

Purist step counters engage in the least intensive self-tracking usage. They are most likely only to track step count and distance traveled. This low-scale use is also reflected in the technologies involved: nearly all *purist step counters* only rely on the functionalities provided by their smartphones and do not use any other devices, such as smartwatches or fitness trackers. *Purist step counters* will only sometimes discuss their self-tracking in personal conversations. Also, engagement with algorithmic feedback is not necessarily part of these users' engagement with self-tracking. Accordingly, two-thirds of *purist step counters* do not even have any goals set regarding their physical activity tracking.

Nonetheless, even the mere registration of bodily parameters can be pleasurable and lead to a feeling of control (Lomborg et al., 2018). Their independence from algorithmic feedback and set goals could also be interpreted as high intrinsic motivation, which does not need extrinsic rewards from technology or others. However, this study saw medium physical activity levels among this cluster. Therefore, future longitudinal studies will need to test whether this type of self-tracking usage might suffice to enhance physical activity.

6. Limitations and directions for future research

Of course, each study comes with its limitations. In this cross-sectional survey, we can only provide a snapshot of self-tracking usage that is perfectly confounded with the single user due to the cross-sectional nature of our data. We cannot rule out the possibility that these three types could be stages in adopting and appropriating self-tracking technologies into users' lives. As we did not ask for the length of time users are already engaging in self-tracking, we cannot test the effects of this on the types. But we recommend that future studies should integrate such a measure. Future studies could also benefit from the triangulation of several (longitudinal) methods, including repeated in-situ self-assessments like experience sampling or log data, to disentangle types from adoption and appropriation processes.

Nonetheless, the detailed view we took on actual usage styles beyond the simple question of usage and non-usage can provide essential insights to assess better the (possibility of) positive and negative effects of self-tracking in various user groups. These groups can extend well beyond young adults, including patients with chronic conditions like diabetes, who need to self-manage and regulate their lifestyles. Future studies should hence integrate more diverse user groups and take further concepts into consideration. For example, users' general innovativeness (Rogers, 2003) or overarching privacy concerns (Schomakers et al., 2018) could influence both user types and stages in the adoption and appropriation process. The same might be true for health status, eHealth literacy, or gender roles.

In addition, this study concentrated on potential positive and negative outcomes of algorithmic feedback, i.e., reactance and perceived social norms. Future studies should extend this view on adverse outcomes and include constructs such as an illusion of control or a decreasing trust in one‘s own body. This could also be done in qualitative interviews to elaborate on young users' awareness and reflections about the potential consequences of self-tracking.

Beyond the effects of algorithmic feedback, also the effects of conversation should be investigated. As our data show, interpersonal talks are prevalent among all usage types and warrant more scholarly attention. In addition, future research into the conversation part of self-tracking should also investigate elements of gamification and competition among users. Building upon first empirical investigations (Hassan et al., 2020; von Entress-Fürsteneck et al., 2019), it will be exciting to see how different gamification elements support different types of self-tracking, interpersonal talks and different stages in the adoption and appropriation process of self-tracking technologies.

Still, we have gained important insights into users' multifaceted self-tracking usage, considering their engagement with different modes of self-tracking and their entire mobile media ecologies. This nuanced view showed that different types of self-tracking usage are more or less susceptible to both the negative and positive effects of self-tracking. Future research taking such a perspective will help us better explain the hitherto inconclusive empirical evidence on the effects of self-tracking physical activity. In addition, taking such a nuanced perspective toward technology use will prevent further technology-deterministic tendencies in assessing the potential capacities of self-tracking technologies. Therefore, we call for more longitudinal empirical research to evaluate detailed self-tracking usage and its possible effects on physical activity, self-perception, overall well-being, etc.

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