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Distal and proximal factors of wearable users' quantified-self dependence: A cognitive-behavioral model

Jiaqi Liu[1] and Shuang Chen[1]

Abstract

Objective: While using self-tracking devices for physical health has become ubiquitous, the potential for quantified-self (QS) dependence as a detrimental outcome for mental health is under-explored. This study examined the mechanism of wearable users' QS dependence by investigating both the distal and proximal factors based on a cognitive-behavioral model.

Methods: A total of 535 wearable users aged 18–35 years were surveyed in this study. The surveys included control variable questions related to age, gender, monthly income, BMI, and wearable use experience. Key variable measures included distal factor (habitual use of wearables), proximal factors (perceived external regulation, recognition, and perceived irreplaceability), and perceived QS dependence. Structural equation modeling (SEM) was used to test research hypotheses.

Results: The results revealed that habitual use of wearables as a distal factor alone was negatively associated with perceived QS dependence. However, it positively influenced perceived external regulation, recognition, and perceived irreplaceability, which in turn significantly contributed to perceived QS dependence, suggesting the suppression effect of the proximal factors.

Conclusions: The relationships between habitual use of wearables and QS dependence are complex. Although habitual use may seem apparently harmless, it can indirectly foster maladaptive cognitions, thereby promoting dependence. These findings underscore the potential threats of maladaptive cognitions that may arise from leveraging technology to promote physical health, thus offering guidance to technology designers for interventions.

Keywords

Self-tracking, quantified-self dependence, habitual use, perceived external regulation, recognition, perceived irreplaceability

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Introduction

As mobile technology has penetrated all aspects of our daily lives, wearables have gained widespread popularity worldwide.[1] Around 150 million wearables were shipped globally in the third quarter of 2023 alone,[2] and the leading tracking app MyFitnessPal has more than 200 million active users all over the world.[3] It reveals a current ubiquitous trend where people are actively engaging health tracking practices with digital devices, which has been conceptualized as quantified-self (QS).[4,5] QS refers to the representational sum of an individual's self-tracking data of any kind—biological, physical, behavioral, or environmental—and is often used as a synonym for self-tracking.[6–8]

QS has been validated to have some positive influence on users.[9,10] Recent empirical results show that digital

[1]School of Journalism and Communication, Tsinghua University, Beijing, China

Corresponding author:
Shuang Chen, School of Journalism and Communication, Tsinghua University, No. 30 Shuangqing Road, Haidian District, 100084 Beijing, China.
Email: chenshuanghere@163.com

data from QS can promote users' health consciousness, knowledge, efficacy, and socio-cultural norms, which improve their physical activity.[11–15] With these outcomes, Maturo and Setiffi[15] declared that QS is a way to combat with today's major risk factors for health burdens, such as obesity,[16] lack of sleep,[17] and uncertainty.[18]

Although existing empirical studies tend to have considered QS from a positive perspective,[11,12] the dark sides of this everyday behavior are also beginning to receive attention. For example, envy,[19] social overload,[20] and privacy invasion[21] are only some of the potential negative impacts of QS, which may in fact bring significant threat to users' well-being.[21] Of the various negative outcomes associated with QS, dependence as a detrimental aspect for mental health is rarely explored. The present study adopted a cognitive-behavioral model (CBM) to examine factors associated with QS dependence, by investigating both the distal factor (i.e. habitual use of wearables) and proximal factors (i.e. perceived external regulation, recognition, and perceived irreplaceability) on the intrapersonal, interpersonal, and human-computer interaction levels.

QS dependence

QS is not merely about self-logging for health; it is also a motivational process that utilizes gamification and social feedback as two fundamental functions.[22] On one hand, gamification refers to designing information systems to afford experiences and motivations similar to those inherent in actual games, but in a non-gaming context, with the intent to change users' behavior.[9] In QS, various gamification stimuli such as points, leaderboards, and likes are employed to enhance users' motivation and encourage sustained engagement.[22,23] However, research has shown that leveraging these gamification features to gain extrinsic reward not only undermines intrinsic enjoyment of activities,[24] but also creates a risk of dependence as users may find it difficult to stop participating in such gamified actions.[25] On the other hand, social feedback from others also plays an important role in QS.[26] Social feedback, whether directly from the tracking device or through the social media it may be connected to, has been identified as a key aspect of QS adoption and a significant motivator for physical activity.[11,22] However, through the everyday performative use of self-tracking data, social feedback also has been identified to increase users' dependence.[26] Therefore, as QS technology combines health tracking with gamification and social feedback functions, the mechanism of QS dependence under its growing popularity requires further examination.

Based on relevant literature, QS dependence can be defined as an excessive reliance on tracking devices.[27,28] QS dependence is characterized by an increased cognitive occupancy of tracker-related thoughts, and decreased motivation to engage in physical activity when the tracker is not involved.[29] Researchers have adopted catchy phrases to describe this phenomenon, such as "I track, therefore I walk"[29] or "working out for likes."[22] These phrases highlight such a distorted psychological state where tracking itself becomes the focus, underscoring people's dependence on QS technologies to motivate their physical activity. Similar to other kinds of problematic media use, QS dependence also represents a significant potential risk to users' mental health.[30,31]

Previous research on the factors influencing QS dependence is limited, with only a few studies providing partial evidence of its effects.[5,22,26,29,32] In a cross-sectional study, continued exercise intention was found to be determined by the continued use of QS, which is influenced by social feedback.[22] Meanwhile, another experiment demonstrated that wearable devices could have a long-term impact on users' perception of exercise even after they no longer use them.[32] This practice has been found to be addictive, becoming companions and extensions of participants' physicality through habitual use in everyday life.[26] Given the limited yet significant research findings on QS dependence, there is a pressing need to develop not only a theoretical framework to better understand the underlying mechanisms but also robust methodologies for future research and practical interventions.

Distal factor of QS dependence

In this study, we adopted the cognitive-behavioral model (CBM) as our theoretical background. CBM was first proposed by Davis[33] to examine the mechanisms involved in problematic Internet use, and later provided a framework for investigating users' problematic use behavior across various media technologies.[34–36] According to CBM, both distal and proximal factors contribute to problematic use.[33]

The distal factor in CBM, which refers to technology usage, is the necessary root factor of problematic use behaviors.[33] When applying CBM, it has been argued that habitual use more appropriately reflects the characteristics of dependence as a distal factor[37] especially as mobile devices emerge.[38] Habitual use as a behavioral routine is characterized as an automatic response that is repeated in specific situations to obtain certain goals or end states.[39,40] The effect of habitual use on media dependence has been validated by an increasing number of studies.[38,41] For example, habitual use was identified as a vital distal factor of social media dependence through the increase of distorted cognitions.[37] In line with this, habitual use of wearables should be recognized as a distal factor of QS dependence.

Proximal factors of QS dependence

In CBM, proximal factors refer to maladaptive cognitions that also contribute to a problematic use behavior.[33] From this perspective, problematic use is viewed not simply as behavioral dependence, but rather as a pattern of technology-related cognitions that result in negative outcomes.[36] Rather than setting specific variables, CBM highlights the crucial role of maladaptive cognitions as a set,[35] which are influenced primarily by technological experiences. Thus, when applying CBM to QS dependence, we must further consider the different affordances of the technology in order to reveal the existing specific maladaptive cognitions on the intrapersonal, interpersonal, and human-computer interaction levels.

On the intrapersonal level, perceived external regulation refers to the way in which one behaves in response to external motivations, specifically to gain rewards or avoid punishment.[42,43] The decline of intrinsic motivation in response to external rewards has been the subject of empirical examinations over the years.[44,45] It should be noted that perceived external regulation can be dynamic and influenced by the use of technology. Even though QS has the potential to support users' self-regulation by enabling users to track their progress, set goals, and receive feedback, it could simultaneously increase individuals' external regulation.[26,46] In this regard, LaRose et al.[40] found that habitual use can undermine individuals' self-oriented goals and lead to an increase in addictive behaviors. In the field of physical activity, while habitual use of QS for rewards such as points and leaderboards, wearable users reported a decrease in intrinsic motivation and higher external regulation as to physical activity.[12,47,48] In addition, it has been demonstrated that perceived external regulation played a predictive role in QS dependence related to physical activity.[29] Consequently, our hypotheses were formulated as follows:

H1a: Habitual use of wearables is positively associated with perceived external regulation.
H1b: Perceived external regulation is positively associated with QS dependence.

On the interpersonal level, gaining recognition from others due to the social feedback can significantly affect one's use behavior,[20] and following self-determination theory, this relates to one's need for competence and social relatedness.[45] Wearable users usually need to quantify their physical activity and share it frequently to get "like" and "comment" from others as approval.[22,26] Therefore, recognition has been identified as the main social aspect of QS, which is positively associated with the use of QS.[49,50] In parallel, it has been identified that social interaction in interpersonal networks can shape one's media dependence.[51] Research has shown that the level of recognition needs fulfilled by social media is directly proportional to addiction.[52,53] Therefore, wearable users can also easily develop dependence through the social feedback in QS. More specifically, we posited:

H2a: Habitual use of wearables is positively associated with recognition.
H2b: Recognition is positively associated with QS dependence.

Moreover, it's important to note that recognition is likely to be associated with perceived external regulation,[54] as previous literature has highlighted its social influence on self-regulation.[26,55] Thus, H3 was as follows:

H3: Recognition is positively associated with perceived external regulation.

Concerning the human-computer interaction level, perceived irreplaceability refers to the perception that media technologies all have unique values and cannot be replaced by other tools,[37] which reflects the psychological hook that attributes unique values to an addiction behavior.[56] Perceived irreplaceability as a technical attribute has been identified as not only a key factor associated with wearable technology adoption intention,[57] but also a negative effect that makes users feel dependent through daily habitual use.[32,58] Empirical studies have further validated the significant role of perceived irreplaceability in fostering different kinds of media dependence, including social media,[37,59] online games,[60] and short-form videos.[61] As Davis[33] argued that dependence behavior impedes one's capacity to solve problems and adopt new behavior, perceived irreplaceability as an instrumental and emotional bond also exists in fostering QS dependence in physical activity. Consequently, the following hypotheses were formulated:

H4a: Habitual use of wearables is positively associated with perceived irreplaceability.
H4b: Perceived irreplaceability is positively associated with QS dependence.

Based on the theoretical and empirical framework, this study investigated both distal and proximal factors that may influence the levels of QS dependence among wearable users. It was further hypothesized that perceived external regulation, recognition, and perceived irreplaceability as three proximal factors would be significant mediators in the relationships between habitual use and QS dependence (see Figure 1):

H5: Perceived external regulation, recognition, and perceived irreplaceability would mediate the relationship between habitual use of wearables and QS dependence.

Methods

Sample and procedure

Participants were recruited by a professional Chinese online research company (https://www.sojump.com) which administers an online subject pool of over 2.6 million Chinese participants featuring a wide distribution of

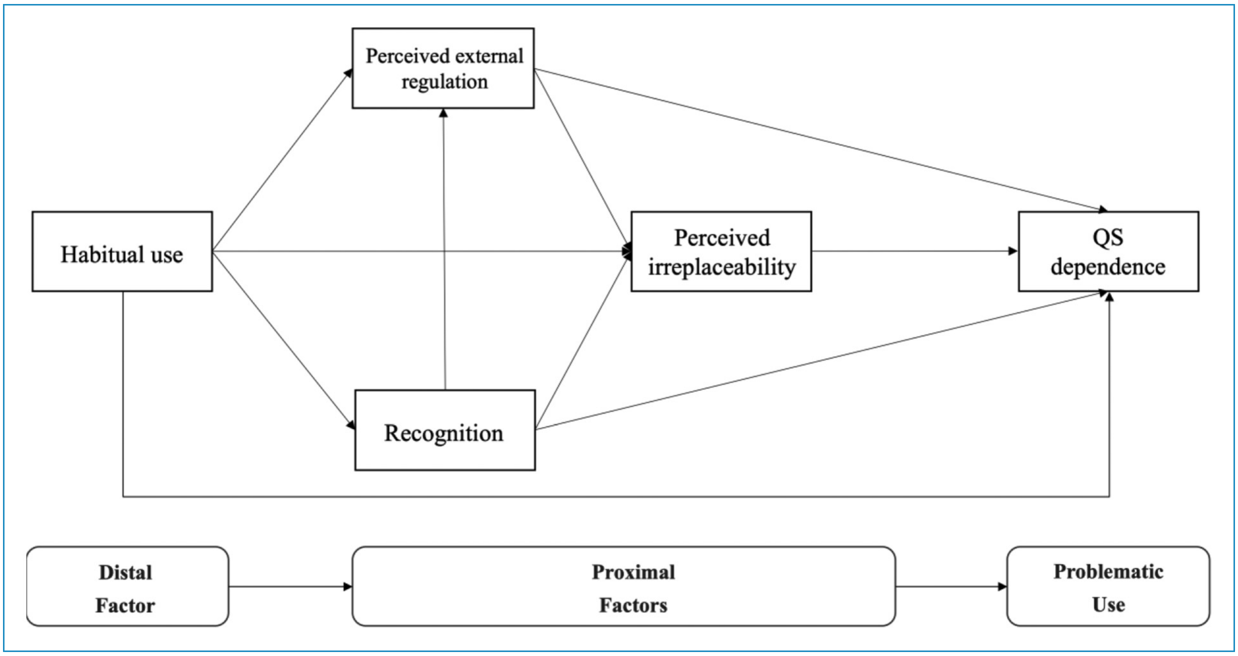

Figure 1. Conceptual framework of the cognitive-behavioral model of QS dependence.

demographics and geographic location. A screening question, "Have you ever used a smartwatch or fitness band to record your physical exercise?" was asked at the very beginning of the survey to screen out unqualified participants. Given that young people are the primary users of wearable fitness technologies,[13,62] young adults aged 18 to 35 were targeted as participants for this study, in line with previous research.[34,63,64] The study sample consisted of 535 participants ($M = 28.46$, $SD = 3.82$). Most participants were female (60.9%), in a relationship (56.30%), had a bachelor's degree (81.5%), with BMI (Body Mass Index) ranging from 15.43 to 47.34, with a monthly household income of 10,000 to 20,000 Chinese yuan (45.20%), and used wearables for more than a year (56.3%).

Measures

Habitual use of wearables. Participants answered four items regarding their habitual daily use of wearables based on the Habitual Use Scale,[40] which has been adapted for QS.[46] Each item was rated using a seven-point Likert scale ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree") (e.g. "The use of a tracker is part of my usual routine."). Previous studies have validated that the scale is a reliable instrument.[37,40,46] The Cronbach's α of the scale was 0.70 in this study.

Perceived external regulation. A four-item scale was used to measure participants' external regulation regarding physical activity (e.g. "I am physically active or exercise because I have to do it"), which was based on the Situational Motivation Scale.[42] Each item was rated on a seven-point scale ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree"). Previous studies have validated the scale in the physical activity context.[29,65] The Cronbach's α of the scale was 0.67 in this study.

Recognition. Four items were modified based on the Recognition Scale[50] to assess participants' social recognition experience while self-tracking (e.g. "I feel good when my fitness achievements in trackers are noticed" and "I like it when my friends comment and like my usage in my fitness data"). Each item was rated using a seven-point Likert scale ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree"). The scale has been validated and shown good reliability in previous research.[20,22] The Cronbach's α of the scale was 0.81 in this study.

Perceived irreplaceability. Three items from the Perceived Irreplaceability Scale[37,66] were adopted to measure participants' perceived irreplaceability of wearable devices (e.g. "I could not easily find other tools that would offer as much value as is provided by my tracker"). Participants were asked to indicate their perceived irreplaceability of wearables using a seven-point Likert scale ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree"). Previous studies has validated this scale in the context of media use.[37,59] The Cronbach's α of the scale was 0.79 in this study.

Perceived quantified-self dependence. User's perceived QS dependence was measured with 12 items adapted from the trackers' Dependence Scale.[29] Participants were asked to access their behavioral, cognitive, and affective indicators regarding self-tracking (e.g. "when I do not wear the tracker, I have the feeling that steps or activities are less valuable," "If I do not wear my tracker during a physical activity, I make less effort than if I wore it") using a seven-point Likert scale ranging from 1 ("Strongly Disagree") to 7 ("Strongly Agree"). Previous studies have validated this scale[29,67] and its Cronbach's α was 0.89 in this study.

Control variables. The study controlled for age, gender, monthly income, BMI and wearable use experience guided by prior research.[11,46] BMI ($M = 21.25$, $SD = 3.68$) was measured by dividing the respondents' weight by the square of their height. Use experience ($M = 3.64$, $SD = 1.12$) was measured by asking how long the respondents have used the wearables.

Statistical analysis

Initial data analysis began by gathering the descriptive statistics results to check for normal distribution and identification of outliers. Multi-collinearity was no problem when VIF-values were below 5. Correlations analysis was then conducted using SPSS 29. Structural equation modeling (SEM) using Mplus 8 with a maximum likelihood estimation was performed to investigate the indirect pathways between habitual use and perceived QS dependence. To evaluate the model fit we used the criteria suggested by Hu and Bentler,[68] specifically, cut-off values for the comparative fit index (CFI) and the Tucker–Lewis index (TLI) were both above 0.95, the root mean square error of approximation (RMSEA) was 0.06 or lower, and the standardized root mean square residual (SRMR) was 0.08 or lower. To test for mediation effects, 5000 bootstrap resamples were estimated to obtain the 95% bias-corrected (BC) confidence intervals (CIs).

Results

Descriptive statistics and correlations

As demonstrated in Table 1, habitual use of wearables was positively related to perceived external regulation, recognition, and perceived irreplaceability. Perceived QS dependence was also positively associated with these three proximal factors. However, perceived QS dependence did not have a significant correlation with habitual use.

Hypothesized model

To test the hypothesized model in Figure 1, SEM was used to incorporate all the control and study variables. Estimations of the relationships showed good fit: $\chi^2(15) = 31.452$, $p = 0.008$; CFI = 0.952; TLI = 0.904; RMSEA = 0.045; SRMR = 0.043 (see Figure 2). First, the results showed that habitual use of wearables was positively associated with recognition and perceived irreplaceability, meanwhile there was no significant relationship between habitual use and perceived external regulation. Second, perceived external regulation, recognition, and perceived irreplaceability were positively associated with perceived QS

Table 1. Descriptive statistics and bivariate intercorrelations among study variables.

	M	*SD*	1	2	3	4	5	6	7	8	9	10
(1) Gender	–	–	–									
(2) Age	28.46	3.82	−0.07	–								
(3) Income	2.40	.79	−0.01	0.23***	–							
(4) BMI	21.25	3.68	−0.31***	0.14***	−0.02	–						
(5) Experience	3.64	1.12	−0.08	0.28***	0.35***	0.04	–					
(6) HU	5.82	.68	−0.08	0.17***	0.23***	0.06	0.35***	–				
(7) PER	4.47	.99	−0.12**	0.08	0.07	0.09*	0.00	0.10*	–			
(8) REC	5.42	.91	−0.16***	0.11*	0.11**	0.02	0.13**	0.36***	0.17***	–		
(9) PI	5.04	1.02	−0.07	0.14**	0.18***	−0.01	0.13**	0.36***	0.27***	0.35***	–	
(10) PQSD	4.16	1.01	0.05	−0.01	0.03	0.04	−0.07	0.01	0.37***	0.18***	0.25***	–

$N = 535$.
HU: habitual use; PER: perceived external regulation; REC: recognition; PI: perceived irreplaceability; PQSD: perceived quantified-self dependence.
*$p < 0.05$. **$p < 0.01$. ***$p < 0.001$ (two-tailed).

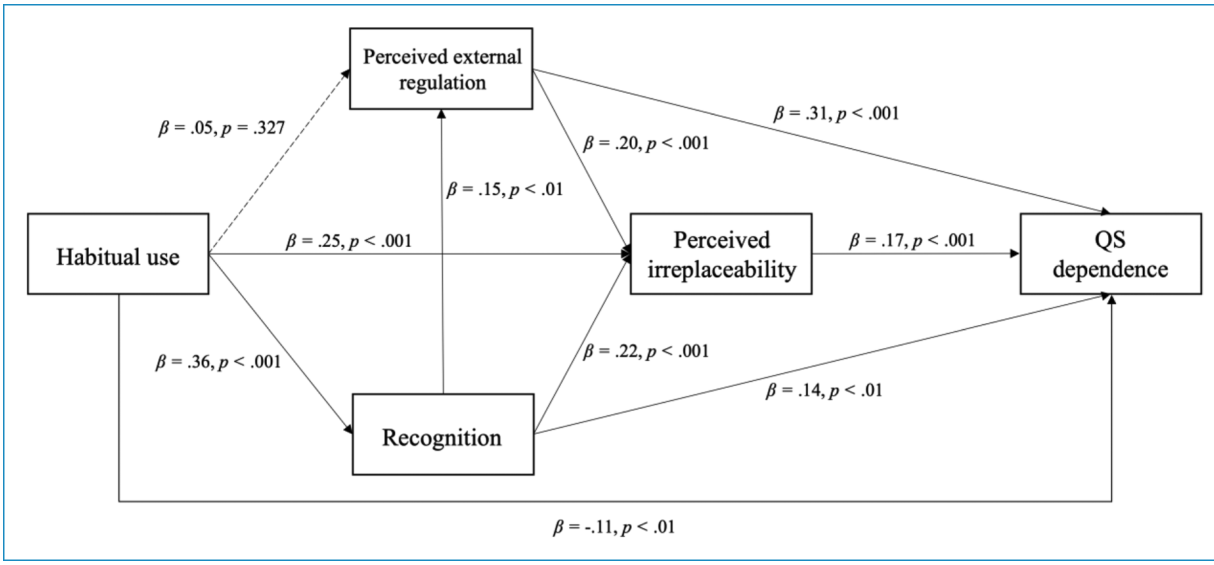

Figure 2. Final SEM model on main study variables.
$N = 535$. Coefficients are standardized.

dependence. Perceived external regulation and recognition were positively associated with perceived irreplaceability. Moreover, recognition was significantly associated with perceived external regulation. Therefore, H1 was partially supported while H2, H3, and H4 were fully supported.

The mediating effects of these proximal factors (i.e. perceived external regulation, recognition, and perceived irreplaceability) between habitual use and perceived QS dependence were tested using the bootstrap method with 5000 iterations. Table 2 showed that the direct effect of habitual use and that the total indirect effects of proximal factors were both significant. Specifically, perceived external regulation did not significantly mediate the relationship between habitual use and perceived QS dependence. Moreover, the mediating roles of recognition and perceived irreplaceability in the relationship between habitual use and perceived QS dependence were significant. Taken together, the addition of three proximal factors to the model resulted in a significant increase in the estimated coefficient linking habitual use to perceived QS dependence, with the direct and indirect effects almost counterbalancing each other. Therefore, our results identified the suppression effect[69] of three proximal factors. H5 was partially supported.

Discussion

Based on CBM, we established a comprehensive theoretical framework to investigate both distal and proximal factors of perceived QS dependence on the intrapersonal, interpersonal, and human-computer interaction levels. As expected, habitual use of wearables, as a distal factor, can influence proximal factors (i.e. perceived external regulation, recognition, and perceived irreplaceability) to indirectly contribute to users' perceived QS dependence. Contrary to our hypotheses, habitual use was directly negatively related to perceived QS dependence and was not directly associated with perceived external regulation. These findings enhance our understanding of the mechanisms of perceived QS dependence, providing guidance for users to promote physical health through technology while minimizing mental health risks.

Theoretical implications

Despite the many positive aspects of QS,[12,23,70] the current study highlights its negative outcome from the perspective of dependence. It contributes to the QS literature by examining how distal and proximal factors contribute to dependence, thus extending the application of CBM in the QS context. Since it was first proposed in the context of traditional Internet use, CBM has proven to be valid in opening up numerous new research trajectories into a wide variety of media. The framework in this study corresponds with the assertion of Davis[33] that technology usage is an underlying factor that indirectly influences users' problematic use through maladaptive cognitions, addressing an existing gap in QS research.

On the intrapersonal level, the current study found no empirical support for a relationship between habitual use and perceived external regulation, with recognition fully mediating this relationship. One explanation may lie in the features of QS habitual users who simultaneously hold two contradictory thoughts: autonomous motivation and external motivation.[12] On one hand, consistent with the theory of self-regulation, QS has the potential to support users' self-regulation through tracking data and

Table 2. Hypotheses testing results.

		β	p-value	95% CI	Decision
Total direct effect		−0.11	0.008	[−0.192, −0.030]	√
Total indirect effect		0.15	<0.001	[0.096, 0.199]	√
H1	HU → PER	0.05	0.327	[−0.044, 0.149]	×
	HU → REC	0.36	<0.001	[0.263, 0.447]	√
	HU → PI	0.25	<0.001	[0.161, 0.342]	√
H2	REC → PER	0.15	0.001	[0.057, 0.240]	√
H3	PER → PI	0.20	<0.001	[0.120, 0.284]	√
	REC → PI	0.22	<0.001	[0.126, 0.315]	√
H4	PER → PQSD	0.31	<0.001	[0.227, 0.396]	√
	REC → PQSD	0.14	0.002	[0.053, 0.231]	√
	PI → PQSD	0.17	<0.001	[0.085, 0.258]	√
H5	HU → PER → PQSD	0.02	0.338	[−0.014, 0.050]	×
	HU → REC → PQSD	0.05	0.003	[0.019, 0.088]	√
	HU → PI → PQSD	0.04	0.002	[0.020, 0.076]	√
	HU → PER → PI → PQSD	0.002	0.365	[−0.001, 0.007]	×
	HU → REC → PI → PQSD	0.01	0.006	[0.006, 0.026]	√
	HU → REC → PER → PQSD	0.02	0.007	[0.007, 0.032]	√
	HU → REC → PER → PI → PQSD	0.002	0.038	[0.001, 0.005]	√

$N = 535$. Coefficients are standardized.
Habitual: habitual use; PER: perceived external regulation; REC: recognition; PI: perceived irreplaceability; PQSD: perceived quantified-self dependence.

personal goals, potentially improving their ability to self-regulate.[40,71] On the other hand, people may not directly gain external regulation by habitual use since they perceive the feedback of QS as external motivation rather than usage itself.[12,29] Therefore, habitual use can influence user's perceived external regulation only in the presence of recognition through social feedback and rewards in QS. Furthermore, the serial mediation model involving perceived external regulation and recognition confirms that both self-oriented and social-oriented factors can work together to influence dependence.[43]

Regarding the interpersonal level, our results support the hypothesis that recognition is positively associated with perceived QS dependence. Building on previous evidence that recognition gained from social network could change user's attitude and behavior in exercise gamification,[22] our study further uncovers the dependence outcomes within this process. This finding aligns with empirical studies which highlighted that recognition and social needs are central predictors of social media addiction.[52,53] Given that exercise exhibits a contagion effect in social networks,[72] other social influences in perceived QS dependence such as social norms[73] and social comparison[11] warrant further investigation.

On the human-computer interaction level, perceived irreplaceability serves as a key factor contributing to perceived QS dependence. It mediates not only the relationship between habitual use and perceived QS dependence but also between the other two proximal factors and perceived QS dependence. Such findings echo those of Wang, Lee[37] and Liu, Lin[59] who identified the perceived irreplaceability as a proximal factor of social media dependence. It also suggests that both intrapersonal and interpersonal factors can lead to perceived irreplaceability in the human-computer interaction level as the most proximal factor of perceived QS dependence. This can be understood by considering that multi-attributes surrounding wearable technology can be perceived and jointly influence the overall technical perception,[57] such as motivational attribute[23,67] and health attribute[57] on the intrapersonal level, as well as social attribute[10] on the interpersonal level.

More importantly, while most of our findings were as expected, the direct path between habitual use and perceived QS dependence exhibited an unexpected negative relationship. This intriguing result reveals the double-edged sword effect of the habitual use of wearables. On the one hand, the negative direct effect of habitual use on perceived QS dependence observed in this study aligns with previous research, suggesting that habitual use alone has very low risk of problematic use[39,41] and may even decrease the possibility of dependence since users expend less cognitive effort to engage in participatory actions.[47] It also hints the potential existence of unexamined mediating pathways, such as adaptive cognition and intrinsic motivation.[74]

On the other hand, the suppression effect of these proximal factors implies that there exist inherent risks associated with maladaptive cognitions and dependence, even though habitual use of wearables may appear to be normal and routine. Exposure to various overlapping media forms in QS, such as gamification elements[10,23] and social network sharing both online and offline,[22,72] has the risk to exacerbate dependence within the complex real-life context. These results resonate with CBM research findings,[37,38] emphasizing that compared to distal factors, maladaptive cognitions as proximal factors play a more significant role in the formation of problematic use.

Practical implications

The findings of this study also have practical implications for wearable users, technology designers, and health professionals. Wearable users can gain a better understanding of their perceived QS dependence, making them more mindful of their tracking habits. Since habitual use is negatively related to dependence directly, individuals could instead focus on the “exercise habit” rather than the “tracking habit”[29] or the “sharing habit,”[22] thereby gradually fostering their intrinsic motivation and autonomy for exercise and modifying problematic use. Technology designers can implement intervention strategies based on CBM that address both distal and proximal factors. This is crucial to maximize the positive effects of wearables while minimizing the negative aspects that result in dependence, given the lack of effective restrictions to address this issue. For health professionals, incorporating gamification into physical health programs requires careful attention to potential discomfort factors on the intrapersonal, interpersonal, and human-computer interaction levels to ensure that benefits to physical health do not compromise users’ mental health.

Limitations and future research

The present research was limited by several factors. First, due to the inherent limitations of cross-sectional survey research, the effects of the variables may be bidirectional. Further longitudinal and experimental studies should be conducted to establish a more robust causal relationship between QS use and dependence. Second, we only address the negative aspect of QS in this study, which may overlook the beneficial aspects of habitual QS use. Since habitual use is not necessarily positive or negative, there are unexamined mediating factors exist within the proposed mechanism that have positive potential, such as self-regulation and competence need.[26,75] It is also possible that QS would benefit certain people more, such as individuals who want to lose weight[76] or have high autonomous motivation for health management.[23] Future research should identify boundary conditions and involve more moderating variables to investigate competing mechanisms. Third, the perceived QS dependence measurements employed in this study are relatively new, and their reliability and validity still require further validation. This measurement only reflects the participants’ perceived QS dependence, acknowledging the subjective nature of self-report methods, which may differ from external observers due to self-interpretation and social desirability. Therefore, there is a need for methodological improvements, such as combining the use of self-report measures with objective data taken from wearable devices.[77] Finally, the sample in this study was composed exclusively of wearable users and young adults from China, which narrows the generalizability of the findings to tracking apps on smartphones, different age groups, and across diverse cultural contexts. The heterogeneity among users of different brands of tracking devices also remains unexplored. Future research may address these limitations by conducting cross-cultural studies or by examining the mechanisms in different age groups.

Conclusion

This study is the first to examine the mechanism of QS dependence by applying the CBM as the theoretical background. Our findings suggest that habitual use of wearables alone will not directly increase user’s perceived QS dependence. Instead, the relationship between habitual use and perceived QS dependence is built through perceived external regulation, recognition, and perceived irreplaceability, all of which indirectly contribute to perceived QS dependence. As QS becomes increasingly prevalent in daily routines, future research should continue to investigate the mechanisms which underly the impacts of habitual tracking on QS dependence to promote physical health while minimizing mental health risks in the digital era.

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Guarantor: SC

ORCID iD: Jiaqi Liu https://orcid.org/0000-0002-6445-8083

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References

1. Burford K, Golaszewski NM and Bartholomew J. "I shy away from them because they are very identifiable": a qualitative study exploring user and non-user's perceptions of wearable activity trackers. *Digital Health* 2021; 7: 1–10. 20211120.
2. Laricchia F. Quarterly wearables shipments worldwide 2014-2023, by vendor, https://www.statista.com/statistics/435933/quarterly-wearables-shipments-worldwide-by-vendor/ (2023, accessed 28 Mar 2024).
3. Curry D. MyFitnessPal Revenue and Usage Statistics (2024), https://www.businessofapps.com/data/myfitnesspal-statistics/ (2024, accessed 28 Mar 2024).
4. Ajana B. Digital health and the biopolitics of the Quantified Self. *Digital Health* 2017; 3: 1–18.
5. Feng S, Mantymaki M, Dhir A, et al. How self-tracking and the quantified self promote health and well-being: systematic review. *J Med Internet Res* 2021; 23: e25171. 20210921.
6. Maltseva K and Lutz C. A quantum of self: a study of self-quantification and self-disclosure. *Comput Human Behav* 2018; 81: 102–114.
7. DB K and Ruckenstein M. Co-evolving with self-tracking technologies. *New Media & Society* 2018; 20: 3624–3640.
8. Swan M. The quantified self: fundamental disruption in big data science and biological discovery. *Big Data* 2013; 1: 85–99.
9. Koivisto J and Hamari J. The rise of motivational information systems: a review of gamification research. *Int J Inf Manage* 2019; 45: 191–210.
10. Yang H and Li D. Understanding the dark side of gamification health management: a stress perspective. *Inf Process Manag* 2021; 58: 102649.
11. Huang G, Sun M and Jiang LC. Core social network size is associated with physical activity participation for fitness app users: the role of social comparison and social support. *Comput Human Behav* 2022; 129; 107169.
12. Nuss K and Li K. Motivation for physical activity and physical activity engagement in current and former wearable fitness tracker users: a mixed-methods examination. *Comput Human Behav* 2021; 121: 106798.
13. Farivar S, Abouzahra M and Ghasemaghaei M. Wearable device adoption among older adults: a mixed-methods study. *Int J Inf Manage* 2020; 55: 102209. 20200804.
14. Shee SY. Making sense of digital health data: negotiating epistemological tensions of everyday eating in Singapore. *Geoforum* 2022; 136: 92–100.
15. Maturo A and Setiffi F. The gamification of risk: how health apps foster self-confidence and why this is not enough. *Health Risk Soc* 2016; 17: 477–494.
16. Gomez-Del-Rio N, Gonzalez-Gonzalez CS, Toledo-Delgado PA, et al. Health promotion for childhood obesity: an approach based on self-tracking of data. *Sensors (Basel)* 2020; 20; 3778.
17. Karlgren K, Brown B and McMillan D. From self-tracking to sleep-hacking. *Proce ACM Hum-Comput Inter* 2022; 6: 1–26.
18. Rakotonirainy A, Orfila O and Gruyer D. Reducing driver's behavioural uncertainties using an interdisciplinary approach: convergence of quantified self, automated vehicles, internet of things and artificial intelligence. *IFAC-PapersOnLine* 2016; 49: 78–82.
19. Wenninger H, Cheung CMK and Chmielinski M. Understanding envy and users' responses to envy in the context of social networking sites: a literature review. *Int J Inf Manage* 2021; 58: 102303.

20. Huang J and Zhou L. Social gamification affordances in the green IT services: perspectives from recognition and social overload. *Internet Res* 2020; 31: 737–761.
21. Srivastava G, Bag S, Rahman MS, et al. Examining the dark side of using gamification elements in online community engagement: An application of PLS-SEM and ANN modeling. *Benchmarking: Int J* 2023; 30(9): 2921–2947.
22. Hamari J and Koivisto J. Working out for likes: an empirical study on social influence in exercise gamification. *Comput Human Behav* 2015; 50: 333–347.
23. Oc Y and Plangger K. GIST do it! how motivational mechanisms help wearable users develop healthy habits. *Comput Human Behav* 2022; 128: 107089.
24. Pink DH. *Drive: The surprising truth about what motivates us*. Edinburgh: Penguin, 2011.
25. Kim TW and Werbach K. More than just a game: ethical issues in gamification. *Ethics Inf Technol* 2016; 18: 157–173.
26. Kent R. Self-tracking health over time: from the use of Instagram to perform optimal health to the protective shield of the digital detox. *Soc Med+ Soc* 2020; 6(3): 205630512 0940694.
27. Carter M and Grover V. Me, my self, and I (T). *MIS Q* 2015; 39: 931–958..
28. Nawaz S. Rethinking classifications and metrics for problematic smartphone use and dependence: addressing the call for reassessment. *Comput in Hum Behav Rep* 2023; 12: 100327.
29. Attig C and Franke T. I track, therefore I walk – exploring the motivational costs of wearing activity trackers in actual users. *Int J Hum Comput Stud* 2019; 127: 211–224.
30. Yıldırım M, Çiçek İ, Öztekin GG, et al. Associations between problematic social media use and psychological adjustment in Turkish adolescents: Mediating roles of family relationships. *Int J Ment Health Addict* 2023: 1–19.
31. Qi H, Bi C, Kang Q, et al. Far from the future: Internet addiction association with delay discounting among adolescence. *Int J Ment Health Addict* 2024; 22: 1677–1696.
32. Clark M, Southerton C and Driller M. Digital self-tracking, habits and the myth of discontinuance: It doesn't just 'stop'. *New Media & Society* 2024; 26(4): 2168–2188.
33. Davis RA. A cognitive-behavioral model of pathological internet use. *Comput Human Behav* 2001; 17: 187–195.
34. Wu-Ouyang B. Are smartphones addictive? Examining the cognitive-behavior model of motivation, leisure boredom, extended self, and fear of missing out on possible smartphone addiction. *Telemat Inform* 2022; 71: 101834.
35. Gamez-Guadix M, Calvete E, Orue I, et al. Problematic internet use and problematic alcohol use from the cognitive-behavioral model: a longitudinal study among adolescents. *Addict Behav* 2015; 40: 109–114.
36. Haagsma MC, Caplan SE, Peters O, et al. A cognitive-behavioral model of problematic online gaming in adolescents aged 12–22years. *Comput Human Behav* 2013; 29: 202–209.
37. Wang C, MKO L and Hua Z. A theory of social media dependence: evidence from microblog users. *Decis Support Syst* 2015; 69: 40–49.
38. Gong M, Yu L and Luqman A. Understanding the formation mechanism of mobile social networking site addiction: evidence from WeChat users. *Behav Inf Technol* 2019; 39: 1176–1191.
39. Koban K, Stevic A, Matthes J, et al. A tale of two concepts: Differential temporal predictions of habitual and compulsive social media use concerning connection overload and sleep quality. *J Comput Mediat Commun* 2023; 28(2): zmac040.
40. LaRose R, Lin CA and Eastin MS. Unregulated internet usage: addiction, habit, or deficient self-regulation? *Media Psychol* 2003; 5: 225–253.
41. Meier A. Studying problems, not problematic usage: do mobile checking habits increase procrastination and decrease well-being? *Mob MedCommun* 2022; 10: 272–293.
42. Guay F, Vallerand RJ and Blanchard C. On the assessment of situational intrinsic and extrinsic motivation: the Situational Motivation Scale (SIMS). *Motiv Emot* 2000; 24: 175–213.
43. Biggs DP, Mallinson-Howard SH, Jowett GE, et al. Perfectionism and exercise dependence: The role of basic psychological needs and introjected regulation. *Int J Ment Health Addict* 2024; 22: 1568–1581.
44. Cerasoli CP and Ford MT. Intrinsic motivation, performance, and the mediating role of mastery goal orientation: a test of self-determination theory. *J Psychol* 2014; 148: 267–286.
45. EL D and Ryan RM. The "what" and "why" of goal pursuits: human needs and the self-determination of behavior. *Psychol Inq* 2000; 11: 227–268.
46. Stragier J, Vanden Abeele M, Mechant P, et al. Understanding persistence in the use of online fitness communities: comparing novice and experienced users. *Comput Human Behav* 2016; 64: 34–42.
47. Seo D and Ray S. Habit and addiction in the use of social networking sites: their nature, antecedents, and consequences. *Comput Human Behav* 2019; 99: 109–125.
48. Mekler ED, Brühlmann F, Tuch AN, et al. Towards understanding the effects of individual gamification elements on intrinsic motivation and performance. *Comput Human Behav* 2017; 71: 525–534.
49. Ehrlén V. Tracking oneself for others: communal and self-motivational value of sharing exercise data online. *Leisure Studies* 2021; 40: 545–560.
50. Hamari J and Koivisto J. Why do people use gamification services? *Int J Inf Manage* 2015; 35: 419–431.
51. Ball-Rokeach SJ. The origins of individual media-system dependency: a sociological framework. *Communic Res* 1985; 12: 485–510.
52. Ponnusamy S, Iranmanesh M, Foroughi B, et al. Drivers and outcomes of Instagram addiction: psychological well-being as moderator. *Comput Human Behav* 2020; 107: 106294.
53. Foroughi B, Griffiths MD, Iranmanesh M, et al. Associations between Instagram addiction, academic performance, social anxiety, depression, and life satisfaction among university students. *Int J Ment Health Addict* 2021; 20: 2221–2242.
54. Mitchell R, Schuster L and HS J. Gamification and the impact of extrinsic motivation on needs satisfaction: making work fun? *J Bus Res* 2020; 106: 323–330.
55. Ryan RM, Kuhl J and Deci EL. Nature and autonomy: an organizational view of social and neurobiological aspects of self-regulation in behavior and development. *Dev Psychopathol* 1997; 9: 701–728.
56. Grau C. Irreplaceability and unique value. *Philosophical Topics* 2004; 32: 111–129.
57. Zhang M, Luo M, Nie R, et al. Technical attributes, health attribute, consumer attributes and their roles in adoption intention of healthcare wearable technology. *Int J Med Inf* 2017; 108: 97–109.

58. Lomborg S, Thylstrup NB and Schwartz J. The temporal flows of self-tracking: checking in, moving on, staying hooked. *New Media & Society* 2018; 20: 4590–4607.
59. Liu Z, Lin X, Wang X, et al. Self-regulation deficiency in predicting problematic use of mobile social networking apps: the role of media dependency. *Decis Sci* 2020; 53: 827–855.
60. Gong X, Chen C and MKO L. What drives problematic online gaming? The role of IT identity, maladaptive cognitions, and maladaptive emotions. *Comput Human Behav* 2020; 110: 106386.
61. Zhang X, Wu Y and Liu S. Exploring short-form video application addiction: socio-technical and attachment perspectives. *Telemat Inform* 2019; 42: 101243.
62. Laricchia F. Wearable ownership in the U.S. 2023, by type and age, https://www.statista.com/statistics/1425005/wearable-ownership-by-type-and-age-us/ (2024, accessed 11 Jul 2024).
63. Canhoto AI and Arp S. Exploring the factors that support adoption and sustained use of health and fitness wearables. *J of Market Manage* 2016; 33: 32–60.
64. Huang ZH, Ma CZH, Wang LK, et al. Real-time visual biofeedback via wearable ultrasound imaging can enhance the muscle contraction training outcome of young adults. *J Strength ConditionRes* 2022; 36: 941–994.
65. Standage M and Duda JL. Validity, reliability, and invariance of the Situational Motivation Scale (SIMS) across diverse physical activity contexts. *J Sport Exerc Psychol* 2003; 25: 19–43.
66. Subramani M. How do suppliers benefit from information technology use in supply chain relationships? *MIS Q* 2004; 28(1): 45–73.
67. Attig C and Franke T. Why do people abandon activity trackers? The role of user diversity in discontinued use. *Int J Hum–Comput Inter* 2022; 39: 1662–1674.
68. Lt H and Bentler PM. Cutoff criteria for fit indexes in covariance structure analysis: conventional criteria versus new alternatives. *Struct Equation Model: Multidiscipl J* 1999; 6: 1–55.
69. MacKinnon DP, Krull JL and Lockwood CM. Equivalence of the mediation, confounding and suppression effect. *Prev Sci* 2000; 1: 173–181.
70. Jin D, Halvari H, Maehle N, et al. Self-tracking behaviour in physical activity: a systematic review of drivers and outcomes of fitness tracking. *Behav Inf Technol* 2020; 41: 242–261.
71. Bandura A. Social cognitive theory of self-regulation. *Organ Behav Hum Decis Process* 1991; 50: 248–287.
72. Aral S and Nicolaides C. Exercise contagion in a global social network. *Nat Commun* 2017; 8: 14753.
73. Sun Y and Zhang Y. A review of theories and models applied in studies of social media addiction and implications for future research. *Addict Behav* 2021; 114: 106699.
74. Shamloo ZS and Cox WM. The relationship between motivational structure, sense of control, intrinsic motivation and university students' alcohol consumption. *Addict Behav* 2010; 35: 140–146.
75. Xi N and Hamari J. Does gamification satisfy needs? A study on the relationship between gamification features and intrinsic need satisfaction. *Int J Inf Manage* 2019; 46: 210–221.
76. Qin Y, Wang X and Namkoong K. A meta-analysis of the overall effect of mHealth physical activity interventions for weight loss and the moderating effect of behavioral change theories, techniques, and mobile technologies. *Mobile Media Commun* 2021; 10: 337–359.
77. Mao C, Bayer JB, Ross MQ, et al. Perceived vs. Observed mHealth behavior: a naturalistic investigation of tracking apps and daily movement. *Mob Med Commun* 2023; 11: 526–548.