Psychological Mechanisms of Personal Health Information Management Technology in Promoting User Health Behaviors: An Empirical Study Based on Smart Wearable Health Products (Postprint)

Authors: Li Caining, Bi Xinhua, Wang Yawei

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Abstract

[Purpose/Significance] This study investigates the psychological mechanisms through which personal health information management technology, based on intelligent wearable health products, promotes users' health behaviors.

[Method/Process] Grounded in the Stimulus-Organism-Response theoretical framework, a path model is established to illustrate how technical elements of intelligent wearable health products influence health behaviors via user psychological variables. Using smart bracelet users as the survey population, data were collected through questionnaires and analyzed using partial least squares structural equation modeling to validate the proposed theoretical model.

[Results/Conclusions] The data management and social interaction functionalities of intelligent wearable health products promote users' health behaviors through inspiration and empowerment. Additionally, the behavior control function enhances users' health behaviors through empowerment. Based on these findings, the paper discusses theoretical contributions and practical implications for the field of personal health information management, particularly regarding research on intelligent wearable health products.

Full Text

The Psychological Mechanisms of Personal Health Information Management Technologies for Promoting User Health Behavior: An Empirical Study Based on Smart Wearable Health Products

Li Caini[1], **Bi Xinhua**[1], **Wang Yawei**[2]
[1]School of Management, Jilin University, Changchun 130025
[2]School of Information, Beijing Wuzi University, Beijing 101126

Abstract:
[Purpose/Significance] This study investigates the psychological mechanisms through which personal health information management (PHIM) technologies promote user health behavior, focusing on smart wearable health products. [Method/Process] Grounded in the stimulus-organism-response theoretical framework, we propose a path model in which technical elements of smart wearable health products influence health behavior through user psychological variables. Using smart wristband users as survey respondents, we collected data through questionnaires and validated the proposed theoretical model using partial least squares structural equation modeling. [Result/Conclusion] The data management and social interaction functions of smart wearable health products promote user health behavior through inspiration and empowerment. Additionally, behavior control functions promote user health behavior through empowerment. Based on these findings, we discuss theoretical contributions and practical implications for the PHIM field, particularly regarding smart wearable health product research.

Keywords: personal health information management technology; smart wearable health products; psychological mechanisms; health behavior; stimulus-organism-response

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1. Introduction

Personal information management research aims to understand the various behaviors surrounding individual information and address related problems [1]. In recent years, with the global rise of chronic diseases and increasing public health awareness, personal health information management (PHIM) research has garnered widespread attention from both academia and industry [2]. Currently, PHIM research is in the conceptualization stage [3]. Most existing studies have employed qualitative methods to investigate PHIM needs and characteristics across different populations (e.g., A. Turner et al. [2], Y. Feng et al. [5]), with limited research exploring the mechanisms through which PHIM influences individual health behavior [6]. Compared to qualitative research, quantitative methods can analyze large-scale samples, overcome researcher subjectivity, and yield more generalizable conclusions. Therefore, this study adopts a quantitative approach to explore the theoretical explanations for how PHIM promotes individual health behavior, thereby extending and deepening existing PHIM research.

PHIM technology refers to information tools that support PHIM activities. In recent years, with the proliferation of mobile internet and advances in health information technology, consumer-oriented PHIM technologies have emerged [2], providing a broad practical foundation for PHIM research. Among these, smart wearable health products (SWHP) have developed rapidly, with leading technology companies such as Google, Apple, Xiaomi, and Huawei launching smart wristband products with health-related functions.

SWHP provide unprecedented support for consumers to engage in PHIM activities, 主要体现在四个方面: First, SWHP automatically monitor and record user health-related parameters through integrated biosensors, reducing the burden of health information collection. Second, SWHP employ intelligent algorithms to process sensor data and output meaningful health information, such as activity levels, energy expenditure, heart rate, and sleep patterns, providing technical support for users to analyze their health status. Third, SWHP typically support users in setting health behavior goals and provide feedback or virtual rewards based on goal achievement. Fourth, SWHP support users in forming or joining communities for health information sharing and exchange.

However, statistics show that over one-third of consumers abandon SWHP within months of purchase [8]. This widespread discontinuance has led some scholars to question whether SWHP can effectively promote user health behavior and whether the SWHP industry can sustain its development [9]. Therefore, investigating whether and how SWHP can promote user health behavior change is crucial for the continued prosperity of the SWHP industry.

A. Chib et al. [10-11] propose that mobile health research (including SWHP) has evolved through three stages: input-mechanism-output. In this framework, input refers to technical elements, mechanism refers to users' psychological processes, and output represents ultimate user health outcomes. The mechanism stage, which connects input and output from a socio-psychological perspective, is critical for theoretically improving technical elements and enhancing health outcomes. However, existing research notes that SWHP studies have focused heavily on technical factors while lacking corresponding mechanism research [12].

Based on this research and practical background, this study addresses the following question: As an emerging PHIM technology, what psychological mechanisms enable SWHP to influence user health behavior?

2. Theoretical Foundation and Literature Review

2.1 Stimulus-Organism-Response Model The stimulus-organism-response (S-O-R) model is a classic theory in consumer behavior research [13] that depicts how external factors (stimulus) influence behavior (response) through the mediation of individuals' internal psychological variables (organism). This model provides a theoretical framework for explaining how information technology affects user behavior [14-16]. Scholars have specifically applied the S-O-R model to SWHP user behavior research to analyze how SWHP technical features influence user attachment [17] and discontinuance [18].

Building on previous research, this study employs the S-O-R model to construct a theoretical framework in which SWHP technical elements (stimulus) influence user health behavior (response) through users' internal psychological variables (organism). Unlike existing literature that focuses on SWHP usage behavior, this study further examines how SWHP promotes user health behavior, shifting focus from intermediate outcomes (technology use) to final outcomes (technology benefits).

2.2 SWHP Technical Elements (Stimulus) This study defines SWHP as commercial-grade wearable electronic hardware devices and their applications for health management. We analyze the currently mature and widely used smart wristband as an example.

Under the influence of technology, culture, policy, and other factors, SWHP have become increasingly popular among consumers. Scholars have summarized SWHP technical elements using inductive and deductive approaches. For example, G. Villalobos et al. [19] analyzed 209 PHIM applications (including smart wristband apps such as Fitbit) and identified 12 technical elements: reminders, goal setting, encouraging messages, action commitment, feedback, historical records, monitoring, rewards, sharing, performance, challenges, and information interaction. T. James et al. [20] categorized SWHP technical elements into three types based on motivation theory: data management, behavior control, and social interaction (see [Figure 1: see original paper]).

Data management includes collection (automatic monitoring, input, integration with other applications), analysis (historical data trends, exercise performance), updating (real-time activity data, goal progress), and searching (exercise tutorials, routes). Behavior control refers to human-computer interaction designs that reinforce user health behavior, including exercise reminders, virtual rewards, and goal management. Social interaction refers to user-to-user interaction functions, including sharing, encouragement, competition, guidance, and comparison.

T. James et al.'s [20] theoretically-derived three-category approach covers the 12 elements identified by G. Villalobos, offering general representativeness with the advantages of conciseness and high generalizability. This classification method was published in the authoritative information systems journal *Management*

Information Systems Quarterly and was empirically validated in that study [20], confirming its reliability. Therefore, this study adopts T. James et al.'s [20] classification of SWHP technical elements, as shown in [Figure 1: see original paper].

2.3 User Psychological Mechanisms (Organism) A pilot study systematically reviewed 250 existing SWHP literature [12] and found that only a small proportion (2%) examined SWHP user psychological mechanisms. Summarizing these studies, scholars [9, 21-26] primarily explored SWHP's influence mechanisms on user health behavior from three perspectives—motivation, capability, and social influence—based on self-determination theory, planned behavior theory, and social cognitive theory.

(1) Motivation. M. Rupp et al. [24] suggest that SWHP can support users' basic psychological needs (such as autonomy, competence, and relatedness) and health goals, thereby enhancing motivation for health-related behaviors. C. Attig et al. [25] propose a motivational dependency effect, where users' health behavior motivation decreases when SWHP is unavailable. C. Kerner et al. [26] found through experimental methods that after eight weeks of SWHP use, adolescent users' scores for autonomy, competence, and relatedness significantly decreased, reducing intrinsic exercise motivation while increasing amotivation, thus suggesting that SWHP negatively affects adolescents' exercise motivation. M. Patel [9] argues that SWHP have difficulty influencing user health motivation. Clearly, SWHP's impact on user motivation remains controversial and requires further investigation.

To explore whether SWHP can stimulate users' health behavior motivation, this study introduces the psychological variable of *inspiration*. T. Thrash and A. Elliot [27] proposed the concept of inspiration in 2010 to describe motivation arising from individuals' interactions with their environment to improve their current state. They identified three core characteristics of inspiration: transcendence (awareness of better possibilities, such as self-improvement), evocation (inspiration originates from external sources), and approach motivation (intention to actualize new ideas). Information management activities can inspire individuals [28], and some scholars have applied inspiration to PHIM and health behavior research. For example, M. Robinson et al. [29] studied online health information seeking among new mothers and found that messages from similar users could inspire seekers to improve themselves, thereby enhancing mothers' self-efficacy, outcome expectations, and parenting behaviors regarding infant sleep training. S. Chuah et al. [30] incorporated inspiration into valence theory to predict users' continued SWHP use. The context of this study aligns with the three core characteristics of inspiration: as an external source, SWHP may evoke users' awareness of improving their health and stimulate motivation for health behavior. Unlike existing SWHP research that focuses on motivation types (internal or external regulation), the concept of inspiration emphasizes the *emergence* of motivation. Therefore, this study introduces the concept of inspiration.

(2) Capability. SWHP support various PHIM activities and are considered helpful for enhancing users' ability to perform health behaviors. T. Ratz et al. [21] conducted a randomized controlled experiment with elderly populations to examine SWHP's impact on user self-efficacy, comparing an experimental group using SWHP for exercise monitoring with control groups using web logs or delayed intervention. Results showed that self-efficacy changes significantly mediated the effect of experimental grouping on participants' exercise intention, planning, and behavior. E. Nelson et al. [22] introduced the concept of *empowerment* to SWHP user research, representing users' beliefs in achieving health goals and sense of control over health behaviors. Their study found that SWHP elements such as attractiveness, feedback, privacy protection, readability, and gamification positively influenced user empowerment, thereby strengthening health commitment. However, unexpectedly, monitoring—a key SWHP function—did not significantly affect user empowerment. Although the authors attempted to explain this from organizational theory (monitoring may cause user stress and distrust), SWHP is a voluntarily adopted technology, and user reactions should differ substantially from organizational technologies. Therefore, this study introduces the concept of empowerment.

(3) Social Influence. According to planned behavior theory and social cognitive theory, human behavior is determined not only by internal psychological factors but also by environmental influences. Y. Zhu et al. [23] specifically examined the impact of SWHP's social features on user exercise and demonstrated through empirical data that SWHP social sharing and competition functions influence individual exercise intention through the mediation of subjective norms. However, this study did not consider the role of SWHP data management and behavior control functions. Therefore, this study will examine the *normalization* effects of SWHP technical elements on user health behavior.

In summary, the psychological mechanisms through which SWHP promote user health behavior are multifaceted, yet existing findings are fragmented and inconsistent. This study comprehensively examines the inspirational, empowerment, and normalization effects of various SWHP technical elements on promoting user health behavior.

2.4 User Health Behavior (Response) User health behavior refers to various actions users perform to promote their own health, such as WHO recommendations for smoking cessation, reduced alcohol intake, and increased physical activity [31]. Insufficient physical activity is a key risk factor for chronic diseases, mental health issues, and low quality of life. A global report indicates that over one-quarter of adults do not meet recommended physical activity levels for maintaining health [32], such as 150 minutes of moderate-to-vigorous exercise per week [31], 10,000 daily steps, or limiting sedentary time to eight hours per day [33]. SWHP offer multiple functions to help users stay active, including tracking daily steps, distance, active minutes, and calorie consumption; providing exercise goal management across multiple activity modes (setting distance, time, or calorie targets for cycling, running, yoga, etc.) with real-time monitoring and feedback; evaluating exercise performance (cardiovascular fitness, optimal heart rate, running pace); setting sedentary reminders; and offering encouragement and virtual rewards upon goal achievement. While SWHP technology continues to evolve, with some products monitoring heart rate, sleep, blood glucose, stress, and other biomarkers to support comprehensive health management [12], this study focuses on the most widespread, mature, and core function—exercise tracking and support—for exploratory analysis of health behavior.

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3. Research Model and Hypotheses

3.1 Research Model Based on the above analysis, this study develops an S-O-R model of SWHP user health behavior: SWHP technical elements (data management, behavior control, and social interaction) serve as external stimuli that influence user health behavior (exercise level as an example) through user psychological mechanisms (inspirational, empowerment, and normalization effects), as shown in [Figure 2: see original paper].

3.2 Research Hypotheses

3.2.1 Hypotheses on the Influence of SWHP Technical Elements on User Psychological Mechanisms (Stimulus-Organism) Based on a systematic literature review, this study proposes that SWHP technical elements promote user health behavior through inspirational, empowerment, and normalization effects.

(1) Inspirational Effect Hypotheses. Inspiration arises from individual-environment interaction, referring to awareness of better possibilities and motivation to achieve them [27]. Research has found that information management is an important source of inspiration [29]. Self-regulation theory suggests that information from self-observation and judgment can motivate self-improvement [34]. During SWHP use, previously imperceptible or unassessable unhealthy habits (e.g., sedentary behavior, calorie imbalance) are presented to users as quantitative data, potentially inspiring lifestyle adjustments. Additionally, SWHP data management functions, including historical statistics and updates, can provide inspirational cues for health improvement—for example, users might observe statistical data showing that switching from driving to public transportation for commuting achieves calorie balance, inspiring them to change their commute method. Furthermore, SWHP's interactive behavior control functions (goal management, activity reminders, rewards) can help users self-inspire and take proactive responsibility for their health [30]. Finally, SWHP social interaction features (sharing, commenting, competitions) may inspire users to improve themselves by observing and emulating exercise role models in their social circles [35].

Based on the above analysis, we propose the following inspirational effect hypotheses:
H1a: Data management is positively related to inspiration.
H1b: Behavior control is positively related to inspiration.
H1c: Social interaction is positively related to inspiration.

(2) Empowerment Effect Hypotheses. Empowerment refers to users' belief in their ability to influence outcomes and control situations [22]. Information empowerment is considered crucial for enhancing individual or organizational action capacity [36]. In this study's context, SWHP reduce the burden of health data collection through integrated biosensors, enhancing users' ability to control their health status. Second, goal setting improves individual performance [37], and SWHP provide rich goal management functions (guiding users to set daily/weekly/monthly exercise duration or calorie targets) to support health behavior change [38]. Additionally, SWHP personalized reminder functions can enhance users' ability to change unhealthy habits, such as sending messages after one hour of sedentary behavior. Moreover, SWHP real-time feedback on quantified results from health behavior changes (e.g., goal progress, additional calories burned through increased intensity/duration) can enhance user efficacy. Finally, SWHP social interaction functions (sharing, liking, commenting) provide emotional and informational support for promoting health behavior.

Based on the above analysis, we propose the following empowerment effect hypotheses:
H2a: Data management is positively related to empowerment.
H2b: Behavior control is positively related to empowerment.
H2c: Social interaction is positively related to empowerment.

(3) Normalization Effect Hypotheses. Norms refer to individuals' perceptions of external expectations regarding behavior execution and reflect reference group influence on individual decision-making [39]. Some scholars argue that SWHP are not merely information conduits but also information senders that can be perceived as having social roles [40] and persuasive features [41]. Therefore, we propose that SWHP functions implicitly convey expectations for user health behavior, exerting normative effects. Specifically, SWHP's continuous monitoring and feedback of health data imply expectations for maintaining or improving health levels; goal management, reminders, and reward functions imply goals for reinforcing health behavior; and social interaction features (competition, comparison, encouragement) imply expectations for healthier lifestyles from others in users' social circles. Thus, SWHP technical elements can trigger, form, and strengthen users' perceptions of health behavior norms.

Based on the above analysis, we propose the following normalization effect hypotheses:
H3a: Data management is positively related to norms.

H3b: Behavior control is positively related to norms.
H3c: Social interaction is positively related to norms.

3.2.2 Hypotheses on the Influence of User Psychological Mechanisms on Health Behavior (Organism-Response) Inspiration is an intrinsic motivational state [30]. When inspired to achieve a goal, individuals' behavioral systems become activated to drive vision actualization [27]. Self-determination theory suggests that behaviors driven by intrinsic motivation are more likely to be sustained [42]. Research has shown that inspiration correlates with positive behaviors, such as environmental protection [43] and self-improvement [44]. Therefore, we propose:
H4: Inspiration is positively related to user health behavior.

Empowerment describes users' sense of capability and control over their health behavior with SWHP assistance [22]. Planned behavior theory posits that perceived behavioral control influences individual behavior [39]. Social cognitive theory similarly proposes that self-efficacy predicts specific behaviors [45]. Numerous studies have confirmed that individuals' subjective perceptions of capability significantly predict health behavior [21, 23]. Therefore, we propose:
H5: Empowerment is positively related to user health behavior.

Norms refer to users' perceptions of external expectations during SWHP interaction and their motivation to conform to others' expectations. Planned behavior theory [39] emphasizes the influence of subjective norms on individual behavior. Y. Zhu et al. [23] demonstrated that social norms affect SWHP users' exercise intention. J. Kim et al. [46] proposed that subjective norms can predict SWHP users' exercise, sleep, and diet-related behaviors. Based on existing research, we propose:
H6: Norms are positively related to user health behavior.

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4. Research Methods

4.1 Variable Measurement and Questionnaire Design This study's measurement scales were adapted from existing literature and modified appropriately for the SWHP context. Specifically, SWHP technical element measurement items were adapted from T. James et al. [20], with data management, behavior control, and social interaction as second-order formative constructs (see). User psychological variable items were derived from T. Thrash et al. [27] for inspiration, E. Nelson et al. [22] for empowerment, and A. Stibe et al. [47] for norms, all as first-order reflective constructs (see). User health behavior was measured using metabolic equivalents (MET) through the widely used International Physical Activity Questionnaire-Short Form [48], as detailed in .

Since the original items were in English, this study employed back-translation to ensure accuracy. After initial questionnaire design, three scholars from Nanyang Technological University, Chongqing University, and Jilin University reviewed and revised the survey, based on which we streamlined and refined measurement items to ensure scientific rigor. We then invited 40 smart wristband users on social media for a pilot test and adjusted ambiguous or ambiguous expressions. The final questionnaire contained 52 items (including two attention-check questions) in four sections: (1) single-choice questions on basic SWHP usage (usage status, brand, frequency, duration); (2) Likert 5-point scale items measuring SWHP technical elements and user psychological variables (1 = "completely disagree" to 5 = "completely agree"); (3) combined single-choice and fill-in-the-blank questions measuring exercise level (e.g., days of vigorous-intensity exercise in the past seven days and daily duration); and (4) single-choice questions on demographic characteristics (gender, age, education, income) and subjective health status.

4.2 Data Collection The questionnaire was distributed and collected via social media platforms including WeChat, Weibo, QQ, and Keep. To enhance participation, a 2 RMB WeChat red packet was offered for each valid questionnaire upon review. Review criteria included: (1) being an SWHP user; (2) passing attention-check questions; (3) passing reverse-coded items; and (4) absence of obvious unreasonable outliers. The survey collected 641 questionnaires, with 347 deemed valid (54% validity rate). The valid sample exceeded 10 times the maximum number of items or predictor variables, meeting recommended standards for statistical analysis [49].

4.3 Data Analysis The collected data exhibited non-normal distribution characteristics. Model assessment includes reflective and formative indicator evaluation. According to C. Fornell et al. [50], this study is suitable for PLS-SEM analysis. We used SmartPLS 3.3.2 to run the PLS algorithm and bootstrapping to obtain model estimates and significance levels.

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5. Research Results

5.1 Sample Descriptive Statistics As shown in , the sample had a balanced gender distribution, concentrated in the 20-29 age group, mostly with undergraduate or graduate education, and over half with monthly income below 3,000 RMB. These characteristics align with general internet user demographics, indicating representativeness. Although the sample skewed younger, nearly half reported fair or poor health status, demonstrating that user health behavior warrants research attention. Additionally, most respondents used SWHP frequently, with over half having used them for more than one year, indicating participation by active, loyal SWHP users.

5.2 Measurement Model Assessment

5.2.1 Reflective Indicator Model Assessment Reflective construct reliability was assessed using Cronbach's α and composite reliability (CR). As shown in , all Cronbach's α and CR values exceeded the recommended threshold of 0.7, indicating good reliability. Convergent validity was assessed using average variance extracted (AVE), with values between 0.79 and 0.98, meeting the 0.5 recommendation. Discriminant validity was evaluated using the Fornell-Larcker criterion (square root of AVE > inter-construct correlations) and the stricter HTMT criterion [51]. All HTMT values were below 0.62, meeting the 0.85 threshold, indicating good discriminant validity.

5.2.2 Formative Indicator Model Assessment Formative indicator evaluation includes weights, variance inflation factor (VIF), and discriminant validity [52]. As shown in , all formative indicator weights were significant, with first-order sub-dimensions effectively predicting second-order constructs. VIF values ranged from 1.18 to 2.70, below the recommended threshold of 3.3, indicating no problematic multicollinearity. Formative construct discriminant validity was assessed through inter-construct correlations, with all values below 0.5, indicating good discriminant validity.

5.2.3 Common Method Bias Test This study used self-reported questionnaires, potentially introducing common method bias. Following H. Liang et al.'s [53] PLS-based approach, we created a common method factor including all measurement indicators and calculated the ratio of squared factor loadings (${R_1}^2$) to squared correlations with the common method factor (${R_2}^2$). The ${R_1}^2/{R_2}^2$ ratio was 25.03 (0.909/0.036), suggesting no significant common method bias.

5.3 Structural Model Assessment After controlling for demographic characteristics and SWHP attributes, results showed that SWHP data management ($\beta = 0.473$***), behavior control ($\beta = 0.094$*), and social interaction (β =* **0.248***) were significantly positively related to inspiration, supporting H1a, H1b, and H1c. Data management ($\beta = 0.235$*), **behavior control (β = 0.392**), and social interaction ($\beta = 0.145$**) were significantly positively related to empowerment, supporting H2a, H2b, and H2c. Behavior control (β = 0.176**) and social interaction ($\beta = 0.317$***) were significantly positively related to norms, supporting H3b and H3c. However, the relationship between data management and norms was not significant, rejecting H3a.

Inspiration ($\beta = 0.184$***) and empowerment (β = 0.377***) were significantly positively related to health behavior, supporting H4 and H5. However, the relationship between norms and health behavior was not significant, rejecting H6.

The explained variance (R^2) indicates that SWHP technical elements had moderate explanatory power for inspiration (R^2 = 45.5%) and empowerment (R^2 = 40.5%), and low explanatory power for norms (R^2 = 25.6%). The identified psychological variables had low explanatory power for health behavior (R^2 = 29.8%).

Further analysis of indirect effects () revealed that empowerment significantly mediated the effects of data management, behavior control, and social interaction on health behavior. Inspiration significantly mediated the effects of data management and social interaction on health behavior, but not the effect of behavior control. Norms did not mediate any SWHP technical element's effect on health behavior.

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6. Conclusions and Implications

This study constructed and tested a path model of PHIM technology promoting user health behavior based on SWHP. Using the S-O-R framework, we found that SWHP's data management and social interaction functions have inspirational effects that promote user health behavior; data management, behavior control, and social interaction influence health behavior through empowerment; and although behavior control and social interaction affect users' norm perception, norm perception does not significantly influence health behavior.

Theoretical Contributions. This study makes three primary theoretical contributions. First, using the S-O-R model, we established theoretical linkages between SWHP technical input, user psychological mechanisms, and health outcomes, opening the "black box" of how SWHP technical elements (data management, behavior control, social interaction) promote user health behavior. The proposed model will help understand the principles of PHIM technology-promoted health behavior and provide references for future theory-based PHIM technology design and outcome evaluation research. Second, integrating perspectives from self-determination theory, planned behavior theory, and social cognitive theory, we systematically examined the psychological mechanisms of SWHP-promoted health behavior from motivation, capability, and social influence perspectives, addressing the insufficient attention to user psychological mechanisms in existing literature. Notably, we innovatively introduced the psychological concept of "inspiration" to extend existing discussions of internal and external motivation in SWHP health behavior research, offering new avenues for future research. Third, in the novel SWHP technology context, we identified findings inconsistent with previous research: while some studies found that SWHP user norm perception positively correlates with health behavior intention, we found that norm effects insufficiently drive actual health behavior, possibly because health behaviors are not easily observable, weakening social norm influence. This reflects the unique characteristics of the SWHP research context and provides insights for future theory testing and development.

Practical Implications. Our findings offer two practical implications. First, empowerment effects of SWHP technical elements have the strongest impact on user health behavior, followed by inspirational effects, while norm effects are non-significant. Research confirms that information framing affects recipients' cognition, with different expressions of the same content creating cognitive biases [55]. Therefore, PHIM designers should consider framing effects in information push functions, enhancing users' sense of control and efficacy, and using inspirational rather than normative expressions to better promote health behavior. Second, SWHP technical elements can indirectly promote health behavior through inspiration or empowerment, with different elements following different paths. We recommend that PHIM/SWHP developers enrich technical functions and improve human-computer interaction design from dual inspirational and empowerment perspectives, while operators should guide users toward deep engagement with various functions to maximize PHIM technology value.

Limitations. This study has several limitations. First, health behavior was analyzed using exercise level as an example, but exercise patterns differ from other health behaviors such as healthy eating; future research should examine multiple health behavior types. Second, this study used cross-sectional survey data, which cannot reveal longitudinal causal relationships between PHIM technology and user health behavior; future research should employ rigorous longitudinal experiments. Finally, the sample was drawn from social media and skewed toward younger populations; future research should use more rigorous sampling methods or examine specific populations (e.g., elderly users) to test the robustness of our conclusions.

References

[1] ELSWEILER D. Book review_{personal} information management[J]. Information processing & management, 2008, 44(3): 1393-1396.
[2] TURNER M, TAYLOR O, HARTZLER L, et al. Personal health information management among healthy older adults: varying needs and approaches[J]. Journal of the American Medical Informatics Association, 2021, 28(2): 322-333.
[3] KIM S, HUBERT T. Characteristics of personal health information management groups: findings from an online survey using Amazon's mTurk[J]. Journal of the medical library association, 2017, 105(4): 361-375.
[4] ALMALKI M, GRAY K, SANCHEZ F. The use of self-quantification systems for personal health information: big data management activities and prospects[J]. Health information science and systems, 2015, 3(1): S1.
[5] FENG Y, AGOSTO E. From health to performance: amateur runners' personal health information management with activity tracking technology[J]. Aslib journal of information management, 2019, 71(2): 217-240.
[6] YANG Mengqing, ZHU Qinghua. Research on characteristics of personal health information management behavior of online health community users[J]. Library and information service, 2020, 64(1): 105-112.
[7] FENG Y, AGOSTO E. Revisiting personal information management through information practices with activity tracking technology[J]. Journal of the Association for Information Science and Technology, 2019, 70(12):

1352-1367.
[8] ATTIG C, FRANKE T. Abandonment of personal quantification: a review and empirical study investigating reasons for wearable activity tracking attrition[J]. Computers in human behavior, 2020, 102: 223-237.
[9] PATEL S, ASCH A, VOLPP G. Wearable devices as facilitators, not drivers, of health behavior change[J]. Journal of American Medical Association, 2015, 313(5): 459-460.
[10] CHIB A, LIN S. Theoretical advancements in mHealth: a systematic review of mobile apps[J]. Journal of health communication, 2018, 23(10): 909-955.
[11] CHIB A, VAN VELTHOVEN H, CAR J. mHealth adoption in low-resource environments: a review of the use of mobile health care in developing countries[J]. Journal of health communication, 2015, 20(1): 4-34.
[12] LI C, LIN S, CHIB A. The state of wearable health technologies: a transdisciplinary literature review[J]. Mobile media & communication, 2021, 9(2): 353-376.
[13] ARORA R. Validation of an SOR model for situation, enduring, and response components of involvement[J]. Journal of marketing research, 1982, 19(4): 505-516.
[14] XIANG Chunjie, WANG Pingping. Research on multiple adoption behaviors of social media in work contexts: from an S-O-R perspective[J]. Information science, 2020, 38(4): 70-76.
[15] QIN Min, LI Ruonan. Research on the formation mechanism of user contribution behavior in online user communities: from online social support and self-determination theory perspectives[J]. Management review, 2020, 32(9): 168-181.
[16] HUANG Sihao, XIAO Jincen, JIN Yanan. Research on factors influencing consumers' continuous purchase intention on social e-commerce platforms based on S-O-R theory[J]. Soft science, 2020, 34(06): 115-121.
[17] CHO W, LEE K, YANG S. What makes you feel attached to smartwatches? The stimulus-organism-response (S-O-R) perspectives[J]. Information technology & people, 2019, 32(2): 319-343.
[18] WANG Wentao, ZHANG Zhen, ZHANG Kun, et al. Research on smart wristband users' discontinuance behavior integrating SOR theory[J]. Library tribune, 2020, 40(5): 92-101.
[19] VILLALOBOS-ZÚÑIGA G, CHERUBINI M. Apps that motivate: a taxonomy of app features based on self-determination theory[J]. International journal of human-computer studies, 2020, 140: 102449.
[20] JAMES T, WALLACE L, DEANE J. Using organismic integration theory to explore associations between users' exercise motivations and fitness technology feature use[J]. Management information systems quarterly, 2019, 43(1): 287-312.
[21] RATZ T, LIPPKE S, MUELLMANN S, et al. Effects of two web-based interventions and mediating mechanisms on stage of change regarding physical activity in older adults[J]. Applied psychology: health and well-being, 2020, 12(1): 23.

[22] NELSON E, VERHAGEN T, NOORDZIJ M. Health empowerment through activity trackers: an empirical smart wristband study[J]. Computers in human behavior, 2016, 62: 364-374.
[23] ZHU Y, DAILEY S, KREITZBERG D, et al. "Social network-out": connecting social features of wearable fitness trackers with physical exercise[J]. Journal of health communication, 2017, 22(12): 974-980.
[24] RUPP M, MICHAELIS J, MCCONNELL D, et al. The role of individual differences on perceptions of wearable fitness device trust, usability, and motivational impact[J]. Applied ergonomics, 2018, 70: 77-87.
[25] ATTIG C, FRANKE T. I track, therefore I walk—exploring the motivational costs of wearing activity trackers in actual users[J]. International journal of human-computer studies, 2019, 127: 211-224.
[26] KERNER C, GOODYEAR V. The motivational impact of wearable healthy lifestyle technologies: a self-determination perspective on Fitbits with adolescents[J]. American journal of health education, 2017, 48(5): 287-297.
[27] THRASH T, ELLIOT A, MARUSKIN L, et al. Inspiration and the promotion of well-being: tests of causality and mediation[J]. Journal of personality and social psychology, 2010, 98(3): 488-506.
[28] MAKRI S, WARWICK C. Information for inspiration: understanding architects' information seeking and use behaviors to inform design[J]. Journal of the American Society for Information Science and Technology, 2010, 61(9): 1745-1770.
[29] ROBINSON M, KNOBLOCH-WESTERWICK S. Seeking inspiration through health testimonials: improving mothers' self-efficacy, outcome expectations, and behavior in handling children's sleep behavior[J]. Health communication, 2020, 35(12): 1455-1465.
[30] CHUAH S. You inspire me and make my life better: investigating a multiple sequential mediation model of smartwatch continuance intention[J]. Telematics and informatics, 2019, 43: 101245.
[31] WHO. Global recommendations on physical activity for health[M]. Geneva: WHO Press, 2019.
[32] GUTHOLD R, STEVENS A, RILEY M, et al. Worldwide trends in insufficient physical activity from 2001 to 2016: a pooled analysis of 358 population-based surveys with 1.9 million participants[J]. The Lancet global health, 2018, 6(10): e1077-e1086.
[33] YAO J, TAN C, CHEN C, et al. Bright spots, physical activity investments that work: National Steps Challenge, Singapore: a nationwide mHealth physical activity programme[J]. British journal of sports medicine, 2020, 54(17): 1047-1048.
[34] BANDURA A. Social cognitive theory of self-regulation[J]. Organizational behavior and human decision processes, 1991, 50: 248-287.
[35] RUMJAUN A, NAROD F. Social learning theory[M]//AKPAN B, KENNEDY T J. Science education in theory and practice: an introductory guide to learning theory. Cham: Springer International Publishing, 2020: 85-99.
[36] ZHANG Cuijuan, KE Ping, YAO Wei. Knowledge management in the

post-knowledge service era: from digital empowerment to knowledge empowerment[J]. Information studies: theory & application, 2020, 43(9): 17-24.
[37] KLONOWSKI M, PELO R, WILLIAMS N, et al. Intensive goal-directed exercise of control[J]. Journal of cognitive psychotherapy, 1997, 11(3): 183.
[38] MICHIE S, RICHARDSON M, JOHNSTON M, et al. The behavior change technique taxonomy (v1) of 93 hierarchically clustered techniques: building an international consensus for the reporting of behavior change interventions[J]. Annals of behavioral medicine, 2013, 46(1): 81-95.
[39] AJZEN I. The theory of planned behavior[J]. Organizational behavior & human decision processes, 1991, 50(2): 179-211.
[40] KIM K J. Interacting socially with the Internet of Things (IoT): effects of source attribution and specialization in human-IoT interaction[J]. Journal of computer-mediated communication, 2016, 21(6): 420-435.
[41] BARTLETT Y, WEBB T, HAWLEY M. Using persuasive technology to increase physical activity in people with chronic obstructive pulmonary disease by encouraging regular walking: a mixed-methods study exploring opinions and preferences[J]. Journal of medical Internet research, 2017, 19(4): e124.
[42] DECI E, RYAN R. Self-determination theory: a macrotheory of human motivation, development, and health[J]. Canadian psychology, 2008, 49(3): 182-185.
[43] KWON J, BOGER C. Influence of brand experience on customer inspiration and pro-environmental intention[J]. Current issues in tourism, 2020, 24(8): 1154-1168.
[44] FIGGINS S, SMITH M, KNIGHT C, et al. A grounded theory of inspirational coach leadership[J]. Scandinavian journal of medicine and science in sports, 2019, 29(11): 1827-1840.
[45] BANDURA A, FREEMAN W, LIGHTSEY R. Self-efficacy: the exercise of control[J]. Journal of cognitive psychotherapy, 1997, 11(3): 191-215.
[46] KIM J. Analysis of health consumers' behavior using self-tracker for activity, sleep, and diet[J]. Telemedicine and e-Health, 2014, 20(6): 552-558.
[47] STIBE A, OINAS-KUKKONEN H, LEHTO T. Exploring social influence on customer engagement: a pilot study on the effects of social learning, social comparison, and normative influence[C]//2013 46th Hawaii international conference on system sciences. 2013: 2735-2744.
[48] BARWAIS F, CUDDIHY T, TOMSON L. Physical activity, sedentary behavior and total wellness changes among sedentary adults: a 4-week randomized controlled trial[J]. Health and quality of life outcomes, 2013, 11: 183.
[49] HAIR J, SARSTEDT M, RINGLE C, et al. An assessment of the use of partial least squares structural equation modeling in marketing research[J]. Journal of the academy of marketing science, 2011, 40(3): 414-433.
[50] FORNELL C. A second generation of multivariate analysis: classification of methods and implications for marketing research[C]//HOUSTON M J. Review of marketing. Chicago: American Marketing Association, 1985.
[51] HENSELER J, RINGLE C, SARSTEDT M. A new criterion for assessing discriminant validity in variance-based structural equation modeling[J]. Journal of the academy of marketing science, 2015, 43(1): 115-135.

[52] THONG RATTANA P. Assessing reliability and validity of a measurement instrument for studying uncertain factors in Thai rice supply chain[Z]. Business HDR student conference 2010-13. 2010.
[53] LIANG H, NILESH S, QING H, et al. Assimilation of enterprise systems: the effect of institutional pressures and the mediating role of top management[J]. Management information systems quarterly, 2007, 31(1): 30.
[54] CHIN W. Handbook of partial least squares[M]. Berlin: Springer, 2010.
[55] WANG Chongliang, CAO Jindan, WANG Tuan, et al. The effect of information framing on health risk perception and behavior change decision-making[J]. Library and information service, 2020, 64(4): 68-77.

Author Contributions:
Li Caini: topic selection, research framework design, data collection and processing, manuscript writing;
Bi Xinhua: research direction guidance, manuscript revision;
Wang Yawei: manuscript revision.

The following conference announcement was included in the original document but is not part of the academic paper:

Conference Announcement

Academic Symposium on "Planning and Key Issues of Document Information Resource Construction"

Resources are the foundation, cornerstone, and basis for the existence and development of libraries (information institutes, archives, etc.). Resource construction is a core function and key capability of libraries. Facing the "14th Five-Year Plan," library resource construction faces many challenges and requires re-formulating strategic planning and construction strategies. To strengthen exchanges on resource construction strategic planning among libraries nationwide and address key issues for the "14th Five-Year Plan," *Library and Information Service* magazine will hold an academic symposium on "Planning and Key Issues of Document Information Resource Construction" in Dalian, Liaoning from October 28-31, 2021. We welcome scholars, experts, university faculty and students, practitioners, and enterprise representatives from libraries, information science, and archives fields nationwide to participate. We also invite paper submissions, with outstanding papers receiving certificates. Selected excellent papers will be presented at the conference and formally published in participating journals such as *Library and Information Service* and *Knowledge Management Forum.*

Theme: Library Resource Construction Planning and Key Issues
Organizer: *Library and Information Service* Magazine
Host: Dalian University of Technology Library
Time: October 28-31, 2021 (including registration and departure, two-day con-

ference)
Location: Dalian University of Technology
Fees: Registration fee 1,500 RMB/person. Accommodation arranged uniformly at participants' own expense.
Contact: See original announcement for details.

Note: Figure translations are in progress. See original paper for figures.

Source: ChinaXiv — Machine translation. Verify with original.