

Postprint of Meta-Analysis on Quantified Self Influencing Factors Under Multi-Model Fusion

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Abstract

[Purpose/Significance] Investigating the influencing factors of quantified self holds significant practical implications for enhancing national health literacy, elevating individual health awareness, and promoting health behaviors. [Method/Process] This paper conducts a mixed-methods study combining qualitative and quantitative approaches. First, it integrates Time-Specific Self-Regulation Theory (TST), Fogg Behavior Model (FBM), and Reflective-Impulsive Model (RIM) to construct a TST-FBM-RIM model. Subsequently, it screens 32 empirical studies on quantified self from CNKI and Web of Science, extracting 7 dimensions, 13 influencing factors, and 91 independent effect sizes. Finally, employing meta-analytic methods and dividing the process into motivation formation and motivation transformation stages, it examines the 13 influencing factors of quantified self and analyzes the moderating roles of gender differences and age differences. [Results/Conclusions] Except for social norms, all other 12 independent variables exhibit positive associations with quantified self. Gender differences moderate the influences of self-efficacy, perceived value, and social norms on quantified self; age differences moderate the influences of perceived value, perceived ease of use, and perceived usefulness on quantified self.

Full Text

Meta-Analysis of Influencing Factors on Quantified Self Using Multi-Model Fusion

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Abstract:

[Purpose/Significance] Exploring the influencing factors of quantified self holds important practical significance for improving national health literacy,

enhancing individual health awareness, and promoting healthy behaviors. [Method/Process] This study employs a mixed-methods approach combining qualitative and quantitative research. First, it integrates Temporal Self-Regulation Theory (TST), the Fogg Behavior Model (FBM), and the Reflective-Impulsive Model (RIM) to construct the TST-FBM-RIM model. Then, 32 empirical studies related to quantified self were selected from CNKI and Web of Science, identifying 7 dimensions, 13 influencing factors, and 91 independent effect sizes. Finally, using meta-analysis and dividing the process into two stages—motivation formation and motivation translation—the study examines 13 influencing factors of quantified self while analyzing the moderating roles of gender differences and age differences. [Result/Conclusion] Except for social norms, which show no significant relationship, the remaining 12 independent variables all demonstrate positive correlations with quantified self. Gender differences moderate the effects of self-efficacy, perceived value, and social norms on quantified self; age differences moderate the influences of perceived value, perceived ease of use, and perceived usefulness on quantified self.

Keywords: Quantified self; Temporal Self-Regulation Theory (TST); Fogg Behavior Model (FBM); Reflective-Impulsive Model (RIM); Meta-analysis

1.1 Quantified Self

Quantified Self (QS), proposed by *Wired* magazine editors Wolf and Kevin in 2007, refers to understanding one's body and mind through self-tracking and data recording, also known as self-tracking or life hacking. Wolf emphasized that QS can serve as a mirror to promote self-improvement, self-exploration, self-awareness, and self-cognition. While QS focuses on data processing and has been described across multiple disciplines, it lacks a strict definition. Information science views it as a dynamically growing personal information system that enables individuals to intuitively understand their healthy living states through personal data analysis. Biomedical science categorizes it into macro and micro measurements, identifying abnormalities and treatments through data comparison. Data science treats it as a method for systematically describing individual phenomena using large data corpora to express new levels of health norms in finer granularity. Human sociology considers it a personal social practice encompassing social interaction and institutions, facilitating health data exchange through social communication. Social media research views it as a meaningful personal experience related to healthy living, dependent not only on individual cognition and emotion but also on the existing technological context. Social psychology sees it as a process covering data collection, visualization, and cross-linking to discover behavioral correlations and inspire new health behaviors. Engineering technology treats it as a tool that promotes empowerment by providing new knowledge and greater control, offering individuals unlimited opportunities to enhance their quality of life. Clinical psychology views it as

a process of using digital tools and technologies to track and analyze one's body, encouraging individuals to improve self-awareness and optimize personal performance through data.

Based on these perspectives, this study adopts Lupton's definition, conceptualizing "quantified self" as a behavioral pattern shaped by both social interaction and social norms, dedicated to improving individual health literacy through the dynamic process of data collection and reflection.

1.2 Temporal Self-Regulation Theory and Its Application Value in Quantified Self

Temporal Self-Regulation Theory (TST), proposed by Hall and Fong in 2007, is a theoretical framework for explaining individual health behavior patterns [Figure 1: see original paper]. TST integrates research from personality and social psychology, cognitive psychology, behavioral economics, and neuroscience, comprehensively considering temporal dynamics, individual self-regulation, and behavioral tendencies. TST has been widely applied in explaining, predicting, and intervening in health risk behaviors. The theory analyzes both rational and abstract aspects of health intentions while emphasizing the importance of irrational variations in practical applications. For instance, TST reveals that insomnia patients exhibit sleep procrastination due to insufficient self-regulation in resisting the temptation to stay up late, while night-type individuals experience sleep disorders due to circadian misalignment. In predicting health behaviors, TST indicates that heavy episodic drinking largely depends on individual drinking intentions and behavioral tendencies. For intervention, TST emphasizes planning and implementing future behaviors in specific contexts, such as assisting young and middle-aged stroke patients in developing precise rehabilitation exercise plans to enhance execution willingness and cultivate rehabilitation habits.

This study innovatively incorporates TST's temporal perspective to facilitate the development of quantified self time-management strategies. Temporal valence involves subjective assessment of time value in quantified self, while consistency concepts involve maintaining consistent attitudes and behaviors across different time periods. Both factors jointly promote motivation formation—the ability to set goals and expectations in time management. Additionally, ability facilitates behavior formation, and self-regulation promotes reflection and absorption of behavioral feedback to optimize behavior patterns. By comprehensively considering temporal valence, consistency concepts, behavioral ability, and self-regulation, individuals can more flexibly adapt to different contexts to achieve optimal quantified self outcomes.

1.3 Fogg Behavior Model and Its Application Value in Quantified Self

In studying how interactive computing technology influences psychology, Fogg proposed the Fogg Behavior Model (FBM), which states that behavior (B) is de-

terminated by three essential elements: motivation (M), ability (A), and prompt (P)—B=MAP. As shown in [Figure 2: see original paper], when all three elements reach certain levels, individuals are more likely to take action. In FBM, motivation and ability do not always develop synchronously. Ability simplifies behavior execution, while motivation manifests in the background. For example, the rapid development of internet and social media provides a suitable environment for misinformation dissemination (ability), while misinformation exploits psychological mechanisms of pleasure or pain (motivation) to promote sharing behavior. Researchers have used FBM to analyze HPV vaccine acceptance among Nigerian caregivers, finding that location and cost (ability) and community misconceptions (motivation) were primary causes of low vaccination rates. The combination of motivation and ability affects contraceptive use, especially after advertisement exposure (prompt). FBM also guides behavior change strategies and persuasive system design, such as enhancing motivation and ability for elderly home monitoring systems to make behavior change signals effective. It informs mental health app design to change behaviors or attitudes, where encouraging messages enhance motivation, intuitive interfaces improve mood tracking ability, and reminders promote sustained use.

This study innovatively integrates FBM's three core dimensions—motivation, ability, and prompt—to guide individuals in clearly understanding their behavior patterns for healthier choices. Motivation refers to the desire to improve health and quality of life through data recording and analysis. Ability encompasses the skills, knowledge, or resources necessary to perform quantified self. Prompts are external or internal signals triggering quantified self behaviors. By incorporating these dimensions, FBM provides a comprehensive analytical perspective for quantified self formation, helping individuals identify obstacles and opportunities to promote sustained practice.

1.4 Reflective-Impulsive Model and Its Application Value in Quantified Self

The Reflective-Impulsive Model (RIM), proposed by Strack and Deutsch in 2004, explores the mechanisms of reflective and impulsive behaviors in social conduct. As shown in [Figure 3: see original paper], individual behavior is regulated by two interacting systems: the reflective system governed by cognition and the impulsive system triggered by episodic experiences. These systems influence each other during decision-making to jointly determine behavioral outcomes. Behavior generation does not always rely on conscious impulse control but can be achieved through strategic cognitive decisions, where episodic experiences directly guide behavior execution while the reflective system provides foundational support for automated control.

According to RIM, health behavior formation is influenced by both conscious control processes and impulsive tendencies. The reflective system generates behavioral decisions and activates corresponding patterns, but behavioral flexibility can lead to impulsive behaviors due to contextual environments, personality

traits, and emotional states. For example, alcohol promotes impulsive thinking's influence on eating behavior, and individuals with low self-control act more impulsively. RIM explains clinical communication skill development in medical education and reflective smartphone disengagement (RSD). The impulsive system operates through spreading activation (episodic cues), such as young consumers making impulsive purchasing decisions under peer influence. The impulsive system also correlates with positive emotions, which increase implicit attitude predictive validity, enabling rapid and spontaneous actions that form automated behavior patterns, as seen in problematic social media use where the impulsive system causes continuous attention while the reflective system involves cognitive behavioral control. RIM tendencies also associate with self-regulation, where high self-regulation groups focus more on reflection and low self-regulation groups lean toward impulsivity.

This study innovatively integrates RIM's dual behavior modes to reveal conflicts and contradictions in quantified self practice—the trade-off between immediate gratification and long-term goals that creates behavioral uncertainty. Episodic experience-driven tendencies root in desires for immediate satisfaction and short-term benefits, while reflective influences from cognitive decisions stem from considerations of long-term goals and benefits. This dual mechanism jointly affects decision-making, making quantified self formation more complex. Through RIM's lens, individuals can gain insight into internal conflicts during quantified self pursuit and adjust behavior patterns for better self-management.

1.5 Constructing the TST-FBM-RIM Fusion Model

While TST, FBM, and RIM have been widely introduced into health behavior research, few studies combine these three models comprehensively. Therefore, based on in-depth examination of these models, this study constructs the TST-FBM-RIM fusion model [Figure 4: see original paper] to analyze quantified self influencing factors. By integrating core elements from TST, FBM, and RIM, the model aims to provide more comprehensive theoretical support for health behavior research. The fusion model not only focuses on individuals' self-regulation capabilities within specific timeframes but also considers environmental factors and individuals' reflective and impulsive tendencies. This theoretical framework can more accurately identify health behavior influencing factors and provide scientific evidence for effective health interventions.

1.5.1 Motivation Formation Process Based on Temporal Dimension and Decision-Making

Motivation formation is a complex psychological process encompassing comprehensive evaluation of quantified self, careful decision-making consideration, and complex interplay of multiple psychological factors. Consistency concepts (C), temporal valence (T), and cognitive decision-making (R) constitute the core of the motivation formation stage. As shown in [Figure 4: see original paper], consistency concepts (C) ensure continuity, stability, consistency, and logic in the quantified self process, avoiding self-contradictory and

chaotic behavioral decisions. Temporal valence (T) reflects individuals' sensitivity and emphasis on time value, influencing expectations and preferences for behavioral outcomes at different time points. Cognitive decision-making (R), as the rational thinking component, requires individuals to thoroughly collect and analyze relevant information and scientifically evaluate potential behavioral outcomes during motivation formation.

1.5.2 Motivation Translation Process Based on Self-Regulation and Dual-System Support The translation of motivation into quantified self involves the combined effects of ability (A), prompt (P), episodic experience (I), and self-regulation (S). Ability (A) serves as the foundation for behavioral translation, determining whether individuals possess sufficient knowledge and skills to execute quantified self. When ability is insufficient, strong motivation may fail to translate into action. Prompt (P) triggers behavior by activating motivation and prompting action. Episodic experience (I) regulates and reinforces the process, where positive experiences enhance ability while negative experiences lead to behavior interruption or abandonment. Self-regulation (S) enables individuals to maintain behavioral continuity and stability when facing cognitive development imbalances, ultimately achieving quantified self through self-motivation and adjustment.

2.1 Research Methods and Tools

Meta-analysis was first proposed by Glass in 1976, using statistical methods to integrate multiple studies, improve conclusion accuracy and credibility, support re-analysis of existing research, reduce errors, and enhance stability and generalizability. Comprehensive Meta-Analysis Version (CMA) is a commonly used meta-analysis tool capable of processing over 100 data formats. This study used CMA 3.0 for overall estimation and moderation effect testing.

2.2 Data Sources

Literature data were collected from CNKI and Web of Science databases. In CNKI, the search used TS= "quantified self" OR "self-tracking" OR "life hacker" with document type limited to papers, 检索时间截至 2024 年 6 月 1 日, yielding 267 Chinese articles. In Web of Science Core Collection, the search used TS= "quantified self" OR "self-tracking" OR "self-quantification" OR "life hacker" AND "empirical research" with document type limited to academic journals, 检索时间截至 2024 年 6 月 1 日, yielding 562 English articles. After reading titles, abstracts, and full texts, literature was screened according to two criteria: (1) studies must examine quantified self influencing factors with at least one factor; (2) studies must include sample size and correlation coefficients or statistical indicators from which correlations could be calculated. The final sample included 32 articles for meta-analysis (15 Chinese and 17 English) .

shows the literature coding table including authors, publication year, document

type, and influencing factors for each study.

3.1 Data Extraction and Coding

This study coded the 32 sample articles, including study population characteristics, sample sizes, and correlation coefficients. To reduce manual error, samples were recoded after a 15-day interval. Correlation coefficient r was selected as the effect size; when not provided, β , t , F , or r^2 values were converted using the following formulas: $r = [t^2/(t^2 + df)]^{(1/2)}$, $r = [F/(F + df)]^{(1/2)}$, $r = 0.98\beta + 0.05$ ($\beta > 0$), $r = 0.98\beta - 0.05$ ($\beta < 0$)

As shown in , the 32 studies identified 7 dimensions and 13 influencing factors, yielding 91 independent effect sizes with a total sample size of 37,285.

presents the data coding table organized by motivation formation stage (consistency concepts, temporal valence, cognitive decision-making) and motivation translation stage (episodic experience, ability, prompt, self-regulation).

3.2 Heterogeneity Test

Heterogeneity testing determined whether random-effects models were appropriate and whether moderation analysis was necessary. As shown in , except for social norms ($I^2 = 52.375\% < 75\%$), all other 12 factors had I^2 values exceeding 75%, indicating that random-effects models were appropriate.

3.3 Relationship Strength

Relationship strength refers to the magnitude of correlation coefficients. According to Cohen's criteria, $|r| < 0.1$ indicates no correlation, $0.1 \leq |r| < 0.3$ weak correlation, $0.3 \leq |r| < 0.5$ moderate correlation, and $0.5 \leq |r| < 1$ strong correlation. Social norms showed no correlation. Moderate correlations were found for self-empowerment, prior norms, perceived value, social support, and privacy concern. Strong correlations were observed for self-efficacy, continuance intention, perceived enjoyment, perceived ease of use, perceived usefulness, social interaction, and subjective norms.

Sensitivity analysis revealed that removing any single sample produced effect size fluctuations minimal compared to overall effect values, indicating high stability of meta-analysis results.

3.4.1 Moderating Effect of Gender Distribution

Study samples were categorized by gender distribution into female-dominated and male-dominated groups. Moderation analysis showed that gender distribution positively moderated the relationships between self-efficacy, perceived value, social norms, and quantified self.

3.4.2 Moderating Effect of Age Distribution

Samples were divided into younger groups (predominantly ≤ 30 years) and older groups (predominantly >30 years). Age distribution positively moderated the relationships between perceived value, perceived ease of use, perceived usefulness, and quantified self.

3.5 Publication Bias

Fail-safe Number (Nfs) was used to detect publication bias by comparing Nfs with $5k+10$ (where k = number of studies). Except for social norms, all other 12 factors had Nfs values far exceeding five times their original sample sizes, confirming result reliability and excluding significant publication bias.

4.1.1 Motivation Formation Stage

Self-efficacy, self-empowerment, prior norms, continuance intention, and perceived value all showed significant positive correlations with quantified self. Self-efficacy refers to individuals' confidence and belief in completing tasks or achieving goals, representing capability assessment and success expectations. High self-efficacy individuals tend to set higher goals and demonstrate resilience. Self-empowerment is the ability to autonomously control and manage one's behaviors and decisions when facing challenges; higher self-empowerment leads to more active participation and stronger autonomy in quantified self. Prior norms refer to accumulated behavioral experience and recognition of effort expectations before action; higher prior norms increase quantified self engagement as accumulated experience and knowledge enhance confidence when facing new challenges. Continuance intention reflects persistence in maintaining action despite difficulties; stronger continuance intention enables long-term quantified self practice without giving up after setbacks. Perceived value is the importance individuals assign to activities or goals; higher perceived value increases willingness to invest time and effort in quantified self.

4.1.2 Motivation Translation Stage

Except for the non-significant relationship with social norms, perceived enjoyment, perceived ease of use, perceived usefulness, social support, social interaction, privacy concern, and subjective norms all showed significant positive correlations with quantified self [Figure 5: see original paper].

Social norms emphasize perceived social status or widely accepted standards. In quantified self, personal decisions primarily depend on intrinsic motivation and cognitive evaluation rather than merely meeting social expectations. Perceived enjoyment refers to the pleasure and fun experienced during quantified self; higher enjoyment leads to more active participation. Perceived ease of use emphasizes perceived technology difficulty, while perceived usefulness emphasizes perceived improvement in personal capabilities. When individuals believe

quantified self tools are easy to master and can enhance abilities (e.g., improving habits or efficiency), they engage more actively. Social support, representing respect and social identity in social networks, significantly influences user behavior and creates positive cycles where individual success inspires broader community participation. Social interaction refers to expanding information channels and maintaining social connections through quantified self; encouragement and feedback from social networks reinforce quantified self value and commitment. Privacy concern reflects worries about personal information collection, use, and sharing; high privacy concerns may hinder motivation translation into action. Subjective norm represents the degree to which significant others believe one should perform the behavior; positive social influence strengthens determination and facilitates motivation translation.

4.2.1 Moderating Effect of Gender

Gender differences influence self-efficacy, perceived value, and compliance with social norms in quantified self. In gender research, the relationship between self-efficacy and gender is significant. According to gender theory, women face more gender role constraints and stereotypes that affect their self-efficacy. During quantified self, women may doubt their abilities due to traditional gender roles, particularly in data and technology fields, while men show greater confidence. Perceived value is also gendered: women unfamiliar with technology may perceive lower value in quantified self, while men's easier technology adaptation leads to higher perceived value. Social norms reinforce gender role stereotypes; conservative views toward women make it harder for them to overcome low self-efficacy, hindering active participation. Research on gender differences in academic output shows female faculty face disadvantages in human capital and institutional resources while bearing greater family responsibilities, limiting time and energy for research.

4.2.2 Moderating Effect of Age

Age differences moderate the effects of perceived value, perceived ease of use, and perceived usefulness on quantified self. Age significantly shapes perceived value of quantified self outcomes. Younger groups demonstrate high technology acceptance, quickly adapting to tools and appreciating their convenience and utility. Older groups face challenges in technology adoption and proficiency, reducing positive perceptions of ease of use and usefulness. Research shows Chinese highly-cited chemists are younger than their American counterparts, indicating younger scientists' higher activity and innovation. Age also positively correlates with privacy disclosure behavior: younger users share personal data more readily for personalized services, while older users are more cautious due to different privacy risk perceptions and technology trust levels. Additionally, age affects data interpretation and application—younger users leverage data for self-reflection and adjustment, while older users prefer intuitive data presentation.

5.1 Research Value

First, this study innovatively developed the TST-FBM-RIM model, revealing the mechanisms of motivation formation and translation in quantified self. This provides a new theoretical perspective for understanding how individuals improve health through quantified means, enriching quantified self research and offering solid theoretical support for future empirical studies. Second, the study identified 7 dimensions with 13 influencing factors, using meta-analysis to verify their association strengths with quantified self, providing clearer research pathways and theoretical references for scholars.

5.2 Research Prospects

First, create highly consistent time value to facilitate quantified self motivation and enhance health awareness across social groups. Through education and publicity, improve public understanding of health technology. Use case studies and story sharing to demonstrate how quantified self enables concrete life changes. Establish online communities and forums for experience sharing and mutual support. Encourage users to share achievements via social media to obtain support from friends and family. Second, create quality behavioral environments to achieve quantified self and improve population health. Focus on enhancing data security and privacy protection for health quantified self tools while simplifying user interface design. Provide clear guidance to help users quickly master functions for easy health data tracking and management. Offer data visualization and reporting to help users understand health status and trends. Encourage sharing health data with family and friends to strengthen social support and interaction.

5.3 Research Limitations

First, the empirical data scope is relatively limited; despite meta-analysis integration, result generalizability requires further validation with more data. Second, when examining moderating variables, cultural background and education level impacts were not fully considered; future research should explore these potential moderators to expand perspectives. Finally, understanding of interactions and dynamic relationships among influencing factors remains insufficient. Future studies could employ more complex statistical methods like time series analysis or structural equation modeling to explore these complex relationships and provide deeper insights.

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