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Self-quantification and consumer well-being: A meta-analytic review

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Abstract

Self-quantification technology is increasingly and irrevocably transforming consumers' relationships with their own minds and bodies. However, existing research findings on the contribution of self-quantification to consumer well-being are disparate. Given the popularity of self-quantification technology among consumers in the post-pandemic era and its inherent transformative nature, it is surprising that this gap remains unaddressed. To resolve this inconsistency and to examine how and when self-quantification influences consumer well-being, we conduct a meta-analysis of consumer well-being in the context of self-quantification technology. Our findings reveal that self-quantification positively influences consumer well-being. However, self-quantification also negatively affects consumer well-being through body image and self-esteem. The systematic moderation effects of cultural dimensions (e.g., uncertainty avoidance and individualism), prior experience, data sharing, and sample characteristics on the relationship between self-quantification and consumer well-being are also confirmed. While uncertainty avoidance, prior experience, and data sharing accentuate the positive effects of self-quantification on consumer well-being, an individualistic culture attenuates this influence. This study contributes to the consumer well-being literature and extends objectification theory in the context of self-quantification. These findings will guide practitioners and policymakers in devising strategies and policies to allow self-quantification technology to be used in a way that enhances consumers' health and well-being.

KEYWORDS
body image, consumer well-being, meta-analysis, responsible marketing, self-esteem, self-quantification, self-tracking

1 | INTRODUCTION

Particularly in this post-pandemic era, well-being is on many people's minds (Pradhan, 2022). The primary pursuit of health and well-being has fueled the use of wearable smart devices and self-tracking applications (apps), otherwise termed "self-quantification." Self-quantification involves monitoring, measuring, analyzing, and sharing daily activities and behaviors (Lupton, 2016). It has become a cultural phenomenon, with millions of people from large economies embracing it, including those from India, China, the United Kingdom (UK),

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the United States (US), and countries throughout the European Union (Lupton, 2016; Wolf, 2009, 2022). This has made self-quantification the new normal for contemporary consumers.

Statista (2024) reported that the fitness tracker market is projected to reach $74.61 billion in 2024, and there are currently 287 million users of self-quantification devices worldwide, including the 37 million average weekly active users of Fitbit (Laricchia, 2023). Furthermore, self-quantification apps had 368 million users in 2023 (Curry, 2024). Prior studies have found that almost 60% of surveyed participants use tracking devices daily (Ajana, 2020), with the vast majority (87%) of wearable owners using them to track health metrics (Deloitte Insights, 2022). Therefore, self-quantification is a rapidly emerging phenomenon in which consumers are self-quantifying their health and behaviors with the intention of improving their physiological and psychological health and well-being. Companies thus consider self-quantification devices and apps as important offerings to support consumers in enhancing their well-being (Mwangi et al., 2024), and they are increasingly integrating self-quantification features into their product and service offerings.

Considering the growing popularity of self-quantification and the interest of brands and consumers in the technology's inherent transformative potential to influence consumer well-being, the topic has garnered interest in the arenas of industry, academia, and public policy. However, the role of self-quantification in fostering consumer well-being is not yet certain. Studies have shown that self-quantification reduces bedtime procrastination, increases sleep efficiency, encourages the adoption of a healthier lifestyle, increases fitness, and promotes physical activity, thereby having a positive effect on consumer well-being (e.g., Jakowski, 2022; Stiglbauer et al., 2019). In contrast, other studies have posited that self-quantification reduces sleep quality and enjoyment, increases annoyance and anxiety, and can result in disordered eating behavior (e.g., Etkin, 2016; Siepmann & Kowalczuk, 2021). Furthermore, self-quantification has been found to contribute to psychological disorders by triggering anxiety (Rosman et al., 2020), thereby reducing consumer well-being (Kussin & Mitchell, 2022).

Some researchers have further suggested that self-quantification is a primary driver of objectification, which results in the deterioration of consumer well-being (Peterson Fronczek et al., 2022). According to objectification theory, the focus on the body for constant evaluation leads to body image issues and reduced self-esteem (Fredrickson & Roberts, 1997). Self-quantification inherently involves the continuous monitoring and assessment of the body through relevant parameters, which increases body-related awareness, thereby engendering body image concerns. This increased focus on bodily metrics can cause individuals to perceive their bodies as mere objects, putting them under the scanner of constant evaluation. Such objectification of the body causes anxiety stemming from body image concerns, in turn, lowers self-esteem (Baumeister, 1988) and, consequently, diminishes the well-being of consumers (Berry et al., 2021; Peterson Fronczek et al., 2022).

Existing research on the impact of self-quantification on consumer well-being is inconclusive, and it remains unclear as to how and under what conditions self-quantification exerts positive or negative effects on consumer well-being, given the mixed findings in current literature. Self-quantification, in practice, often centers around physical metrics, such as weight, appearance, and fitness levels, which are directly tied to how individuals view and judge their bodies, possibly causing body image issues and lowering the self-esteem of consumers. However, there is a lack of unanimity over the relationship between self-quantification and well-being, which presents a significant challenge to both academics and practice aiming to advance the theoretical understanding and practical application of self-quantification. Thus, examining the mediating roles of body image and self-esteem is critical for understanding the relationship between self-quantification and consumer well-being. To this end, in this meta-analytic review, we show and explain how self-quantification impacts well-being through the mediators. We propose and test a framework that explores consumer well-being, a central component of quality of life (Sirgy, 2012), within the context of a "quantified self" world. Specifically, our research intends to answer the following questions:

RQ1: What is the influence of self-quantification on consumer well-being?

RQ2: Does body image and self-esteem (based on objectification theory) mediate the relationship between self-quantification and consumer well-being?

RQ3: Which moderators are responsible for the heterogeneity in the findings of studies on self-quantification and consumer well-being?

To answer the above three research questions, we propose an objectification theory-based model that synthesizes the extant literature on self-quantification to enhance our understanding of how and when self-quantification influences consumer well-being. First, we propose a conceptual model (see Figure 1) guided by the research questions; subsequently, we conduct a meta-analysis based on 88 studies drawn from 71 articles with 42,102 unique respondents. We conduct a meta-analysis primarily due to two reasons. First, it resolves inconsistencies in the existing literature, stemming from the mixed findings for the effect of self-quantification on consumer well-being. Second, our meta-analysis explains heterogeneity among findings based on the different conditions and contexts under which studies were conducted. Through this, we are not only able to reconcile past findings but also systematically advance knowledge in the domain of self-quantification and consumer well-being (Eisend, 2015; Hulland & Houston, 2020; Paul & Barari, 2022). Unlike previous studies that have explored the impact of self-quantification on any specific aspect of consumer well-being, our meta-analysis provides a comprehensive and aggregated perspective under diverse contexts, which allows us to assess the cumulative evidence and identify trends and patterns without losing any nuances. This holistic approach enables us to identify consistent effects across different contexts and populations, thereby offering robust and generalizable conclusions about the impact of self-quantification on consumer well-being.

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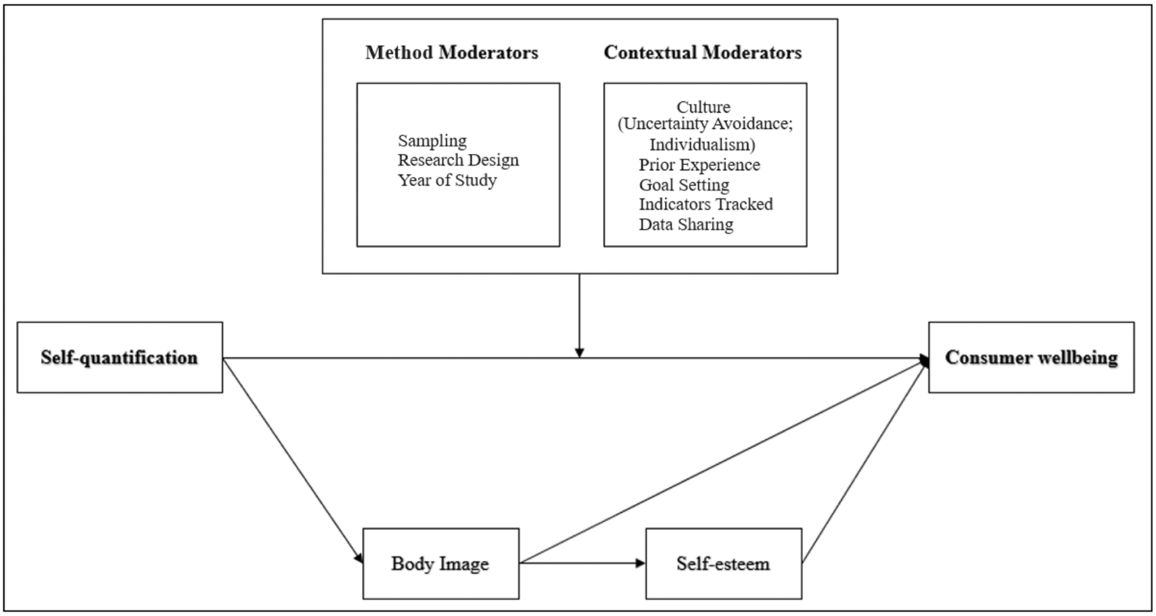

FIGURE 1 Conceptual framework.

The academic contributions of this study are many. First, the findings in the literature about the relationship between self-quantification and consumer well-being were previously inconclusive, and this study resolves the lack of clarity by demonstrating that self-quantification increases consumer well-being. In other words, the current study finds that an emphasis on self-quantification can improve consumers' quality of life (Sirgy et al., 2007) by enhancing their well-being. This finding opens various avenues for marketing scholars, who can work closely with practitioners and policymakers from various fields, such as medicine, health care, leisure and recreation, among others, to develop products and services involving self-quantification to enhance consumers' quality of life.

Second, we explore the relationship between self-quantification and consumer well-being using a self-objectification lens. Our findings suggest that body image and self-esteem mediate the relationship between self-quantification and consumer well-being, extending objectification theory in the self-quantification context. The negative indirect effect of body image reduces the influence of the positive direct effect of self-quantification on consumer well-being. This nuanced insight into the dual effects of self-quantification highlights the complexity and nature of its impact on consumer well-being. Moreover, it underscores the importance of body image and self-esteem as mediators. This result suggests that marketing managers should stay away from body image-related messages in marketing their self-quantification offerings. They should also consider awareness and support programs for countering issues related to body image, such as appearance anxiety or body shame.

Last, this research contributes to the literature on self-quantification and well-being by showing that the associations between the variables in the proposed model vary depending on certain moderating conditions: culture (e.g., individualism and uncertainty avoidance), data sharing, prior experience, and sample selection. Our study uniquely identifies these moderating factors, which have not been systematically explored in extant literature, thus, providing a more detailed understanding of the contingencies under which self-quantification can positively or negatively impact consumer well-being. Practically, this study provides several insightful recommendations for self-tracking companies to help them design effective consumer well-being strategies, as discussed in later sections.

The next section describes the conceptual model for consumer well-being in a quantified-self world. This is followed by the methodology section, which elucidates the data collection process, the inclusion and exclusion criteria, and the data analysis procedures. We then provide the results from the meta-analysis and discuss the implications of our findings for theory and practice. We conclude by describing the study's limitations and directions for future research.

2 | DEVELOPMENT OF CONCEPTUAL FRAMEWORK

We developed a conceptual model of this meta-analysis, as shown in Figure 1. Self-quantification is the focal construct, and its impact on well-being is the main relationship of interest. We explored three sets of variables to address the research questions. First, we examined the influence of self-quantification on consumer well-being. Second, we investigated mediators informed by objectification theory to understand how self-quantification influences consumer well-being. Last, we analyzed moderators to account for varying effects of self-quantification on consumer well-being. Because the literature suggested that antecedents of self-quantification may also influence consumer well-being (Hollebeek & Belk, 2021), we only explored bivariate correlations among the variables. We did not hypothesize

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about these relationships or include them in the structural equation modeling (SEM) test due to a lack of sufficient empirical support for their inclusion in the meta-analysis.

2.1 | Self-quantification

The term "quantified self," first coined in 2007, describes the phenomenon of purposively collecting and tracking data about daily activity using wearable smart devices and self-tracking smartphone apps (Lupton, 2016; Wolf, 2010). For almost two decades, scholars have studied the process of self-quantification in diverse fields, such as information systems, human–computer interactions, marketing, sociology, and psychology. Depending on the field, "self-quantification" is also referred to as "personal informatics," "life-logging," "self-surveillance," "self-tracking," and "self-monitoring" (Lupton, 2016; Maltseva & Lutz, 2018).

Although the term "self-quantification" was coined relatively recently, the practice of collecting and recording data about personal biometrics or daily activities is not new. Individuals have been known to keep handwritten journals or dairies, take photographs, and keep logs of daily activity using head-mounted cameras. With advancements in technology, smart wearables and smartphone apps have revolutionized the practice of self-monitoring. These devices and apps enable the passive monitoring of physiological, psychological, and behavioral changes—a process that is passive in the sense that, with little effort, consumers can track progress in every facet of their lives (Wolf, 2009). Additionally, sophisticated data visualization techniques enable consumers to easily interpret data from wearables and apps (Maltseva & Lutz, 2018). Drawing on prior studies (Choe et al., 2014; Lupton, 2016, 2023), we, therefore, define self-quantification as the process of collecting and interpreting digitized self-tacking data using wearable smart devices and applications to improve well-being. The current research specifically considers the effects of data collection processes (i.e., the act of measurement) and of interpretation (i.e., obtaining feedback from self-quantification devices and apps) on consumer well-being.

To develop our framework, we first considered the direct effect of self-quantification on consumer well-being. We considered the effect of tracking only one kind of indicator at a time on consumer well-being (e.g., the effect of quantifying only dieting behavior or only physical activity) for two main reasons. First, we did so to maintain the parsimony of the model since tracking multiple indicators at a time would make the model too complex due to the presence of individual and interaction effects. To account for the variance in effect sizes due to the tracking of different parameters, we considered indicators tracked as a relevant moderator. Second, due to the unavailability of a sufficient number of quantitative studies (see Table 1) that tested the effects of tracking two or more simultaneous indicators on well-being, drawing meaningful conclusions was not possible. Therefore, we did not account for the simultaneous tracking of multiple indicators in this meta-analysis.

Furthermore, drawing on objectification theory, we conceptualized and examined whether body image and self-esteem mediate the relationship between self-quantification and consumer well-being. Subsequently, to account for the potential heterogeneity in the relationship between self-quantification and consumer well-being, we augmented the conceptual framework using relevant moderators.

Last, the extant literature widely studied the influence of technology adoption factors such as consumer attitude (Brinson et al., 2019), hedonic motives (Dhar & Wertenbroch, 2000; Huta et al., 2012; Voss et al., 2003), perception of privacy (Aboelmaged et al., 2021; Hill et al., 2015), perceived usefulness (Davis, 1989), and social influence (Bonfield, 1974) in self-quantification technology adoption and usage. Because self-quantification affects consumer well-being, it is reasonable to assume that the above factors might also affect consumer well-being (Mwangi et al., 2024). Therefore, we analyzed only the bivariate relationships between these factors and consumer well-being. We did not consider them for inclusion in the structural model due to the limited availability of studies on the relationships between these variables and mediator variables, which in turn limited our ability to draw meaningful inferences. Therefore, we only discuss the associations of these variables with self-quantification and consumer well-being.

2.2 | Self-quantification and consumer well-being

"Consumer well-being" is a state that is characterized by consumer responses to consumption, which includes satisfaction, positive affect, and perception of quality of life (Diener, 2009; Sirgy, 2012; Zhao & Wei, 2019). Although consumer well-being has been well researched, it continues to intrigue academics and practitioners alike. United Nations (UN) Sustainable Development Goal (SDG) 3, "Ensure healthy lives and promote well-being for all at all ages," echoes the importance of well-being in today's world. Individuals are increasingly expected to actively manage their own health and well-being (Ostrom et al., 2021; Pradhan, 2022; Tikkanen et al., 2023). According to a similar definition of the term, "consumer well-being" broadly refers to the well-being of consumers in consumption-related settings (Lee & Ahn, 2016). It encompasses a broad spectrum of cognitive and emotional evaluations of life satisfaction (Balderjahn et al., 2020), pleasure (Seligman, 2011), and perceived quality of life (Sirgy, 2012) achieved through consumption activities (Zhao & Wei, 2019).

The concept of consumer well-being considers consumers' perceptions of their cognitive and affective consumption experiences. Consumer well-being is linked to both physiological and psychological health (Rozanski & Kubzansky, 2005; Su et al., 2014) and with affective responses, hedonism, and quality of life (Diener, 2009). Consumer well-being, therefore, is multifaceted, consisting of multiple dimensions of individual well-being in consumption contexts. Hence, we define "consumer well-being" as individual well-being in the context of consumption, as affected by data collection and data interpretation using self-quantification devices and apps.

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TABLE 1 Overview of the self-quantification (SQ) and well-being (WB) literature.

Study	Key issues/scope	Relationship between SQ and WB	Direction	Forms of WB	Indicators tracked	Sample	Experience	Data sharing	Goal
Boghrati et al. (2024)	Role of emotional tracking	Self-tracking has a lingering effect of positive emotions.	Positive	Satisfaction with life; emotional WB	One	Nonstudent	×	✓	×
Attie and Meyer-Waarden (2023)	Usage of sleep apps by Gen Z	Perceived WB decreases after the use of sleep apps compared to before their use.	Negative	Perceived WB	One	Student	×	×	×
Hallam et al. (2022)	Mental health effects of SQ devices and apps	The monitoring of steps using mobile phones or wrist-worn fitness trackers positively affects mental health and WB.	Positive	World Health Organization (WHO-5) WB index	One	Nonstudent	×	✓	✓
Jakowski (2022)	Role of sleep apps in recovery management	There are no significant differences among sleep indices between users of sleep apps and non-users.	No effect	Sleep quality; daytime sleepiness	One	Nonstudent	×	×	×
Karapanos et al. (2016)	Use of trackers in creating meaningful experiences in everyday life	The experience of doing something about health using activity trackers increases individual WB.	Positive	Individual WB	-	-	-	-	-
Jin et al. (2020)	Effect of SQ in effortful activities	SQ increases enjoyment and subjective vitality—and, hence, WB.	Positive	Enjoyment; subjective vitality (hedonic WB)	One	Nonstudent	×	×	×
Lee & Lee (2021)	Role of SQ devices in improving employees' health	SQ technology positively affects health improvement.	Positive	Health improvement	One	Nonstudent	×	✓	✓
Wolf et al. (2021)	Social interaction feature of wearables	Social interaction features positively affect personal growth and negatively affect life satisfaction.	Mixed	Life satisfaction; personal growth	One	Nonstudent	×	✓	✓
Harvey et al. (2020)	Posture feedback from wearables	Wearable posture feedback devices improve WB.	Positive	WB	One	Student	×	✓	×
De Moya & Pallud (2020)	Effect of SQ practices on consumers	SQ has conflicting effects on consumer WB (13 empowering effects and 11 disempowering effects).	Mixed	Empowerment (self-management); disempowerment (self-objectification)	-	Nonstudent	-	-	-
Wittkowski et al. (2020)	Effect of self-tracking technology on WB	SQ technology does not increase WB and may even undermine advice compliance and, hence, WB.	Negative	Empowerment (personal growth)	One	Nonstudent	×	✓	×
Chuah (2019)	Benefits and risks of SQ technology engagement	Utilitarian motives, hedonic motives, and social motives for using SQ devices result in positive effects on WB.	Positive	Physical WB; psychological WB; social WB	-	Nonstudent	✓	×	×
James et al. (2019)	Consumer goals and consumer wellness	There is a negative effect of body-focused goals on WB.	Negative	Eudaimonic WB	One	Nonstudent	✓	×	✓

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TABLE 1 (Continued)

Study	Key issues/scope	Relationship between SQ and WB	Direction	Forms of WB	Indicators tracked	Sample	Experience	Data sharing	Goal
Ryan et al. (2019)	Emotional regulation in using wearable activity tracking	Using wearable devices is a positive experience for individuals with little risk of negative psychological consequences.	Positive	Positive/negative affect (PERMA model of WB)	One	Nonstudent	✓	×	×
Stiglbauer et al. (2019)	Benefit on health and WB in using SQ devices	Fitness trackers have a positive effect on users' physical health and psychological WB.	Positive	PERMA model of WB	One	Student	✓	×	×
Wulfovich et al. (2019)	Implications of using SQ devices for patients with chronic health conditions	SQ devices and apps improve patients' wellbeing.	Positive	Physical health	One	Nonstudent	✓	✓	×
Kari et al. (2017)	Effect of self-tracking in the short term	Perceived WB effects are minor during the short-term use of self-tracking devices.	Positive	Physical WB; social WB	-	Nonstudent	-	-	-
Etkin (2016)	Consequences of measuring activity or behavior	Measurement of behavior or activity decreases enjoyment and reduces subjective WB.	Negative	Subjective WB	One	Student	×	×	×
Lunney et al. (2016)	Health-related outcomes of SQ use	There is a positive effect of SQ devices on perceived health benefits, such as perceived health improvement, active lifestyle, exercise frequency, and perceived general health.	Positive	Health outcomes	-	Nonstudent	✓	×	×
Nelson et al. (2016)	Role of activity trackers in health empowerment	Wearable smart devices have a positive effect on health empowerment.	Positive	Health empowerment	Many	Nonstudent	✓	×	✓

Abbreviations: PERMA, positive emotions, engagement, relationships, meaning, accomplishments; SQ, self-quantification; WB, well-being.

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Recognizing the multi-dimensional nature of well-being, various fields such as psychology, management, and medicine conceptualize well-being differently, with some overlaps in these conceptualizations (for details, see Mwangi et al., 2024). For example, the PERMA (Positive emotions, Engagement, Relationships, Meaning, Accomplishments) model of well-being and subjective well-being conceptualizations both feature overlapping dimensions like positive emotions and meaning in life. Drawing on the different conceptualizations of well-being used in prior studies examining self-quantification (Etkin, 2016; Hallam et al., 2022; Stiglbauer et al., 2019), we consider concepts such as quality of life (Sirgy, 2012), subjective well-being (Diener, 2009), psychological well-being (Ryff & Keyes, 1995), physical well-being (McKee-Ryan et al., 2005), PERMA well-being (Seligman, 2018), social well-being, and emotional well-being (Siepmann & Kowalczuk, 2021).

While grouping different forms of well-being together raises valid concerns about losing nuances, a preliminary meta-regression analysis (see Supporting Information S1: Appendix A), which considers different measures of well-being as an independent variable and the effect sizes of the influence of self-quantification on well-being as the dependent variable, reveals that this is not the case. The results show no significant dependence on the specific measures of well-being, indicating that there is no significant loss of information due to the grouping process, and the nuances of different aspects of well-being remain persevered even after the grouping process. Thus, our approach allows us to analyze the influence of self-quantification on well-being without losing any information due to grouping different forms of well-being. It ensures simplicity and clarity in generating actionable insights while preserving the information with respect to different aspects of well-being.

Monitoring consumption and/or consumption behavior can affect consumption itself and its related outcomes. Self-quantification devices and apps are linked to health improvement and, therefore, to well-being (Attie & Meyer-Waarden, 2023). The rapid proliferation of wearable technologies over the past decade has resulted in many marketing scholars studying self-quantification behavior and focusing on consumer well-being (Etkin, 2016; Peterson Fronczek et al., 2022; Tikkanen et al., 2023). Consumers can now collect, review, and reflect on data collected by self-quantification devices and apps (Constantiou et al., 2022), which can track consumer biometrics, daily activities, daily goals, and goal progress. Users of self-quantification devices and apps may benefit by gaining insights into the performance of their body, mind, and behavior (Sysling, 2020). Scholars have suggested that self-quantification enhances self-awareness and self-knowledge, with studies reporting that self-quantification increases sleep efficiency, helps in the adoption of a healthier lifestyle, encourages physical activity, reduces anxiety, speeds up recovery, and acts as a resource for consumer agency (e.g., Attie & Meyer-Waarden, 2023; Henkens et al., 2021; Jakowski, 2022; Tikkanen et al., 2023). One of the hallmarks of self-quantification technology is its ability to collect and analyze diverse data about an individual's physiological and emotional state. Wearable devices such as smartwatches, fitness bands, and smart rings have been described as "a dashboard to the body" (Berg, 2017) which have the ability to collect health biometrics and instantly share it with others augmenting the speed of primary healthcare. Given the potential of self-quantification technology to transform a consumer's relationship with their own body (Lupton, 2013), self-quantification can increase an individual's self-awareness and self-knowledge (Ferreira et al., 2021), thereby enhancing well-being. Therefore, we hypothesize:

H1a. Self-quantification increases consumer well-being.

Research regarding the influence of self-quantification on consumer well-being has produced mixed results (Table 1). Reports of wearable smart technologies aiding (Economist, 2022a, 2022b) and hampering (Kussin & Mitchell, 2022; Washington Post, 2022) consumer well-being also have been highlighted by the media. With respect to goal progress and fulfillment, the accomplishment (or lack of accomplishment) of goals may trigger emotional and psychological processes that affect well-being. For example, upon achieving a goal, consumers may experience contentment and the feeling of being in control, thereby enhancing their well-being. However, when goals remain unachieved, consumers may feel stressed out by the objective data, deteriorating their well-being (Constantiou et al., 2022; Hollebeek & Belk, 2021; Seligman, 2018). Thus, self-quantification, in one way or another, influences consumer well-being.[1] Consumers also incur certain costs in the process of self-quantification, which might be financial, social, psychological, and/or physiological (Weathers & Poehlman, 2024). Studies have posited that self-quantification deteriorates consumer well-being by reducing sleep quality, reducing enjoyment, increasing anxiety, causing self-objectification, and leading to disordered eating behavior (e.g., Etkin, 2016; Peterson Fronczek et al., 2022; Siepmann & Kowalczuk, 2021). Self-quantification can undermine motivation and reduce enjoyment (Etkin, 2016), deteriorating well-being. Furthermore, knowledge gained through self-quantification devices can induce anxiety and stress (Tikkanen et al., 2023). Self-tracking consumers may tend to treat their bodies as mere objects (Hoang & Ng, 2023; Peterson Fronczek et al., 2022), which may deteriorate consumer well-being. Accordingly, we hypothesize the following:

H1b. Self-quantification decreases consumer well-being.

2.3 | Mediators: Body-image and self-esteem

Objectification theory suggests that increased and continuous focus on the body may induce body image issues among individuals (Fredrickson & Roberts, 1997). Continuous focus on the body creates

[1]Extant literature on self-quantification and consumer well-being has produced mixed results. Some studies suggest that self-quantification can aid in self-regulation and will enhance consumer well-being (Ferreira et al., 2021; Tikkanen et al., 2023). Other studies suggest that self-quantification can undermine enjoyment and motivation (Etkin, 2016) and body-image-related anxiety (Peterson Fronczek et al., 2022), which deteriorates consumer well-being. Therefore, we advance two competing hypotheses for the effect of self-quantification on consumer well-being.

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an image of an ideal body in consumers' minds and a tendency to constantly compare themselves with the newly formed ideal body image. Specifically, the internalization of the ideal body or external beauty standards leads to body image issues such as appearance anxiety and body shame. Self-quantification devices gather information about a user's physical activity, body weight, calories burned, heart rate, and stress levels, among other parameters. (Berg, 2017; Hoang & Ng, 2023). Stated differently, the devices and apps draw consumers' attention toward their bodies by providing focused feedback and evaluations about bodily functions and behaviors in descriptive (e.g., graphs) and/or numerical forms. Consequently, consumers become more conscious of their own appearance and consumption habits. A consumer's body thus turns into a set of attributes represented merely by numbers (Gittus et al., 2020).

Moreover, wearable smart technology with social networking capabilities enables consumers to compare themselves with a reference group, further shaping their self-perception and affecting their well-being (Hamari et al., 2018). Many self-quantification devices and apps provide a reference point for comparison with peers in the form of the average data of all individuals in a particular demographic. While this may motivate consumers to perform extra activity (Etkin, 2016), it can also induce body image issues (Peterson Fronczek et al., 2022). Regardless of a consumer's physicality, comparison with peers or non-peers is linked to a negative body image (Jones, 2001).

Consumers often adhere to various societal and cultural norms related to physical and behavioral expectations, which are recognized, reinforced, and rewarded by self-quantification devices through haptic feedback, promotional coupons, and push notifications. For example, many self-quantification challenges require users to walk 10,000 steps daily for a week and reward the top performers. When participating in such self-quantification challenges, individuals can compare their performance with that of others. Some consumers even take up the challenge of completing 40,000 steps daily, which can affect other aspects of their lives. In such cases, external norms and expectations drive consumers (Tikkanen et al., 2023), which exacerbates their appearance concerns and lowers their self-esteem, affecting their well-being (Ryan & Deci, 2000).

Self-quantification can make consumers more conscious of their appearance and behavior. Continuous focus only on bodily sensations makes it the center of self-worth, which can be measured precisely with self-quantification devices (Peterson Fronczek et al., 2022) and can distance consumers from achieving a higher level of self-awareness (Baumeister, 1988). However, giving disproportionately high attention to the body can form the perception that self-worth is determined by physical appearance, lowering an individual's self-esteem, especially when consumers have an ideal body image, which often is virtually unattainable. In other words, having a negative body image leaves consumers worried about how others view them, thereby lowering their self-esteem (Ameen et al., 2022).

Body image issues create anxiety among consumers about how their bodies are perceived. Consumers regularly compare themselves with others using the information generated by self-quantification devices, which inhibit consumers' inner-directedness and cause stress (Tikkanen et al., 2023). Idealized images raise comparison standards (Richins, 1991), augmenting body image issues and lowering well-being. Social comparison can also lead consumers to pursue an idealized body image, which can hamper their well-being.

As established, a negative body image can cause consumers to worry about how others view them, lowering their self-esteem (Ameen et al., 2022). This, in turn, induces anxiety, stress, depression, and/or disordered eating (Shea & Pritchard, 2007), harming consumers' well-being. Some consumers even engage in maladaptive coping mechanisms, such as anorexia or bulimia (Thompson & Heinberg, 1999), which further deteriorates their well-being. Self-quantification can reduce consumer well-being by augmenting body image issues and lowering self-esteem. Accordingly, we account for these effects of body image and self-esteem when developing our conceptual framework, and we advance the following hypothesize:

> **H2.** Body image and self-esteem will serially mediate the relationship between self-quantification and consumer well-being. Specifically, self-quantification evokes a negative body image among consumers, which lowers self-esteem and subsequently lowers consumer well-being.

2.4 | Moderators

Meta-analysts suggest identifying variables that may cause inconsistent findings in the literature; these variables not only explain the inconsistencies but also enhance the generalizability of meta-analytic findings across contexts (Hunter & Schmidt, 2015; Van Vaerenbergh et al., 2014). Since meta-analysis synthesizes effect sizes from prior empirical research, identifying moderators is constrained by several factors: (1) the codability of variables from the existing studies, (2) theoretical grounds for selecting variables that can plausibly influence the relationships, and (3) the lack of sufficient empirical studies addressing these relationships (Troy et al., 2008). Due to these limitations, our search for potential moderators was constrained. Consistent with previous meta-analytic reviews published in marketing journals (Ashaduzzaman et al., 2023; Blut et al., 2023; Santini et al., 2023), we developed predictions about whether contextual characteristics (e.g., culture, prior experience, goal setting, indicators tracked, and data sharing) and research design artifacts (e.g., sample characteristics, research design, and year of study) account for between-study heterogeneity. We examined whether the strength of the association between self-quantification and consumer well-being varies under these conditions. However, given the limited empirical research available on the mediating pathway, such as the effect of self-quantification on body image and self-esteem, we did not consider moderators that could potentially influence these effects. Conducting a moderator analysis with a smaller set of studies would lead to spurious inferences due to insufficient statistical power (Troy et al., 2008). In the following section, we provide the rationale for the choice of the moderators.

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2.4.1 | Contextual moderators

"Contextual moderators" refers to the variables that account for different contexts between studies. In the self-quantification literature, studies were conducted under different conditions (see Table 1), and these may account for the between-study heterogeneity. For example, while some studies considered participants from the USA, others drew participants from Korea and India; the cultural differences between participants from different countries may account for varying effect sizes. Moreover, as evident from Table 1, some studies considered participants with prior experience of using self-quantification devices and apps, while others focused on participants who were new to self-quantification. Some studies included participants with a goal—for example, to walk 10,000 steps/day—whereas others included no predefined goal for participants. Furthermore, while some studies tested the effect of diet monitoring on well-being, others instead focused on the monitoring of physical activity. Last, while some studies inhibited the sharing of data with peers (to control its effect), others did not. We thus identified the variables of cultural differences, prior experience, goal setting, type of indicators tracked, and data sharing, and examined whether these conditions could act as moderators.

Culture

Hofstede's (1984) national cultural dimensions of uncertainty avoidance and individualism can account for the varying effect of self-quantification on consumer well-being. Because different studies were conducted with participants from different cultures, the influence of self-quantification on well-being could vary. Therefore, in the current meta-analysis, we used Hofstede's uncertainty avoidance index and individualism cultural dimension to assess the potential implications of culture on the relationship between self-quantification and consumer well-being.

"Uncertainty avoidance" refers to a society's tolerance for uncertainty and ambiguity. Consumers from uncertainty-avoiding societies tend to be more internally driven than consumers from uncertainty-accepting cultures (Hofstede, 1984). Thus, in general, consumers from uncertainty-avoiding cultures are more interested in knowing about themselves than consumers from uncertainty-accepting cultures. Consumers from uncertainty-avoiding cultures seek patterns to avoid risk (Steenkamp et al., 1999). Thus, when consumers from uncertainty-avoiding cultures self-quantify, their well-being is expected to increase. However, when consumers from uncertainty-accepting cultures self-quantify, their well-being is not expected to increase substantially. Hence, we advance the following hypothesis:

> **H3a.** Uncertainty avoidance will accentuate the effect of self-quantification on consumer well-being. Specifically, uncertainty-avoiding cultures will display higher consumer well-being compared to uncertainty-accepting cultures.

"Individualism versus collectivism" refers to the degree to which individuals are an integral part of a group (Hofstede, 1984). Individualistic cultures expect individuals to take care of themselves, as opposed to collectivist cultures, which expect individuals to rely on and contribute to a larger group. Self-quantification devices and apps have features that display the average performance of an individual with respect to their reference or demographic group. Moreover, additional features for sharing data with, observing, and competing with a reference group are available with self-quantification devices. It is reasonable to expect that collectivistic cultures will value these features more than individualistic cultures. Therefore, consumers from individualistic cultures, on account of being detached from in-groups, will not see much enhancement in their well-being when self-quantifying compared to consumers from collectivistic cultures, who benefit from the confirmation of their position within the group and, thus, see greater enhancement in their well-being.

> **H3b.** An individualistic culture will attenuate the relationship between self-quantification and consumer well-being. Specifically, consumers from individualistic cultures will display lower well-being compared to those from collectivistic cultures.

Prior experience

Many past studies have demonstrated that having prior technological experience increases consumers' usage intention, usage behavior, and other related outcomes, such as well-being (Attie & Meyer-Waarden, 2023). Having prior experience with technological devices enhances consumer knowledge, which is stored in the memory and remains accessible to consumers when it becomes relevant (Ajzen & Fishbein, 1969). Moreover, consumers with prior experience in self-quantification are less anxious about any predictable negative experience with self-quantification technology and, therefore, do not experience technology-induced stress (Kumar et al., 2022; Pahi et al., 2024; Tarafdar et al., 2007); thus, they will experience a greater enhancement in well-being. Thus, we hypothesize the following:

> **H4.** Prior experience with self-quantification devices and apps will strengthen the relationship between self-quantification and consumer well-being. Specifically, consumers with prior experience will display higher consumer well-being compared to consumers with no prior experience.

Goal setting

"Goal setting" refers to a researcher providing participants with an activity goal, such as walking 10,000 steps in a day. Goal setting—and the achievement of (or failure to achieve) these goals—may not make individuals happier than they were before if the goal is not in self-concordance (Sheldon & Elliot, 1999). In other words, individuals who are internally driven and who pursue goals set by themselves to satisfy their basic psychological needs are more likely to experience increased well-being. In contrast, a goal set as a part of a study is an externally driven goal, as the researchers—rather than the individuals—set the goal. Although individuals may complete goals because they want to receive rewards or obtain the researchers'

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approval (i.e., social desirability), this may not be enough to cause their well-being to improve. Contrary to this, consumer well-being may increase in the absence of goal setting because participants may set goals in self-concordance. Thus, we posit the following:

> **H5.** Goal setting will attenuate the effect of self-quantification on consumer well-being. Specifically, studies with predefined goals set for participants will display weaker consumer well-being compared to those with no goals set for participants.

Indicators tracked

Self-quantification has a multitude of indicators for physiological and psychological health, which consumers can track (Berg, 2017). Physiological health indicators focus on body measures (e.g., heart rate and steps), while psychological health indicators focus on broader life measures (e.g., mood and stress; Hoang & Ng, 2023). Because the indicators represent different aspects of well-being (i.e., physiological and psychological), we expect they will result in different strengths in terms of the effect of self-quantification on consumer well-being. Prior studies have varied with respect to the types of indicators tracked by participants. For example, some studies considered the effect of monitoring physical activity on well-being (Hallam et al., 2022), while others considered the effect of monitoring diet on well-being (Simpson & Mazzeo, 2017). Thus, we hypothesize the following:

> **H6.** Tracking indicator type (i.e., physiological vs. psychological) will moderate the relationship between self-quantification and consumer well-being.

Data sharing

"Data sharing" refers to the exchange of measured data between different self-quantifying devices or with different people/groups (Almalki et al., 2015). Self-quantification devices and apps have features that allow users to share data across social networks, such as health professionals, family members, and reference groups. Individuals share their achievements and goal completions (e.g., completing a five-mile run). They receive gratification in the form of likes and comments. Through this positive reinforcement, individuals can meet their competence, autonomy, and relatedness needs, which enhances their well-being (Rejikumar et al., 2021; Ryan & Deci, 2017). Thus, data sharing from self-quantification devices and apps will enhance consumer well-being. In the absence of data sharing, however, individuals do not get recognition from reference groups for their milestones. As a result, their need for relatedness and competence may be met, but they are not validated. Thus, we posit the following hypothesis:

> **H7.** Data sharing will strengthen the effect of self-quantification on consumer well-being. Specifically, consumers sharing data will display a greater effect on well-being than will consumers not sharing data.

2.4.2 | Method moderators

Similar to contextual differences, research design choices made by researchers can also account for differences in effect sizes (Van Vaerenbergh et al., 2014). Consistent with prior meta-analytic reviews, we consider methodological differences to be potential moderators affecting the influence of self-quantification on consumer well-being. Specifically, we consider the sample population, research design, and year of study as potential method moderators.

Sampling

Meta-analysis can identify whether the inclusion of a specific population has influenced studies' findings (Iyer et al., 2020; Orsingher et al., 2009). For example, Peterson (2001) showed that the effect sizes for college students and for the general population vary substantially. Researchers have used diverse samples while studying the effect of self-quantification on consumer well-being. Some studies have considered the student population, while others have focused on athletes or patients. Patients, athletes, and older adults tend to use self-quantification devices and apps for specific reasons such as recovery management (Jakowski, 2022), self-healing, and managing their well-being independently (Gimpel et al., 2013). The student population, in contrast, is considered technologically savvy and early adopters of most new technologies. Thus, the student population is extrinsically motivated by what is considered trendy (Pradhan et al., 2023) and is mainly influenced by external factors, such as peer group influence (Kim et al., 2014). Therefore, the student population will display smaller effect sizes as compared to nonstudent populations, such as patients, elderly consumers, or athletes, who are intrinsically driven and have utilitarian motivations such as maintaining or improving fitness and quality of life. Thus, we propose the following hypothesis:

> **H8.** The student (vs. nonstudent) sample population will moderate the relationship between self-quantification and consumer well-being such that for the student sample, the effect of self-quantification on consumer well-being will be smaller than nonstudent samples.

Research design

While some studies used an experimental design to investigate the effect of self-quantification on consumer well-being, other studies implemented the survey method. This could be another reason for the variation in the effect sizes. Experimental studies establish causality, use manipulations, maintain rigor in testing the effect, and control for confounding effects. In contrast, the survey design involves the one-time measurement of variables, which has limitations—such as common method bias—when displaying smaller effect sizes. Thus, on average, we expect studies using an experimental design to display larger effect sizes than studies with a survey design (Farley et al., 1995), on account of controlling for confounding effects. Hence, we propose the following:

H9. Experimental designs, compared to survey designs, will show a larger effect on the relationship between self-quantification and consumer well-being.

Study year

We also consider the varying study periods in explaining the variance in the effect of self-quantification on consumer well-being. With time, the accuracy and precision of self-quantification technology have improved, such as with the inclusion of new sensors, indicators, and a multitude of device attributes (Dooley et al., 2017; Gorzelitz et al., 2020). Also, consumers have become more knowledgeable about and experienced in using self-quantification devices and apps, making them more comfortable with self-quantification. Because consumers examined in studies from long ago—compared to respondents in newer studies—did not have the degree of access to or the precision of today's self-quantification technology, we expect a variance in the effect size. The year of study is used as a continuous variable. Thus, we expect the study period to influence the effect of self-quantification on consumer well-being, and accordingly, we posit the following hypothesis:

H10. Recent studies will display a greater effect between self-quantification and consumer well-being than do older studies.

3 | METHODOLOGY

Using the random effects model, we first examined the associations between several antecedents and consumer well-being. These antecedents included various drivers of self-quantification (e.g., attitude, privacy risk, hedonic motive, social influence, and perceived usefulness), self-quantification, body image, and self-esteem. Furthermore, through the lens of objectification, we probed the indirect effects of self-quantification on consumer well-being through the mediation of body image and self-esteem. For the causal model estimation, we used the meta-analytic SEM (MASEM) approach to examine the influence of self-quantification on both mediators and the dependent variable, following recent meta-analyses published in reputed marketing journals (e.g., Ashaduzzaman et al., 2023; Maseeh et al., 2021). We used the MASEM approach to assess the proposed structural model across various samples and studies. If the proposed model fit the data well across different studies, it was understood to provide strong evidence of the validity of the proposed model (Cheung & Chan, 2005; Jak & Cheung, 2020). Last, we ran a moderation analysis to determine whether the moderators plausibly explained the heterogeneity and contrasting findings (Hulland & Houston, 2020).

3.1 | Search protocol, inclusion and exclusion criteria, and coding process

To collect the relevant empirical research, we did an exhaustive search of relevant literature on multiple electronic databases (e.g., Web of Science, Scopus, ProQuest One Business, INFORMS PubsOnline, EBSCO, and Google Scholar). As previously noted, "self-quantification" using wearable devices and self-tracking apps is also referred to as "self-surveillance," "quantified self," "personal informatics," "lifelogging," and "self-tracking," among other things (Lupton, 2016). As such, we used several keywords to ensure we identified all relevant articles, including the following: "quantified self," "quantified-self," "self quantification," "self-quantification," "quantification of self," "quantified selves," "quantified-selves," "self tracking," "self-tracking," "lifelogging," "life logging," "life-logging," "activity tracking," "fitness tracking," "personal analytics," "personal informatics," "self-monitoring," "self monitoring," "self-surveillance," and "self surveillance."

We additionally included cross-referenced articles and conference papers. We restricted our search to articles published in the domains of business, management, and accounting; psychology; sociology; social science; and medicine. We did this because articles published in other fields, such as engineering or computer science, were not relevant to our research questions. Furthermore, we included articles published in the English language only. After compiling this list, we removed duplicate entries. A total of 1411 articles were retrieved as a part of this search process from the above-mentioned databases. Figure 2 summarizes the search protocol.

We then conducted abstract screening to remove papers that satisfied at least one of the following exclusion criteria: papers that were (1) unrelated to self-quantification, (2) unrelated to consumer well-being, (3) conceptual, review, or qualitative in nature, or (4) quantitative but did not study any relationships between the variables of interest to us. If it was unclear from the abstract whether the article was relevant or not, it was accepted to be transferred to the next stage of the search process. Accordingly, we were left with 137 articles. Peterson and Brown (2005) suggest including multiple effect sizes that are easily convertible into effect size correlations, as this enhances the generalizability of the results. We therefore included studies that reported any of the following: (1) correlations, (2) regression coefficients, (3) t-statistics, (4) chi-squared statistics, (5) odds ratios, or (6) F-statistics between the constructs of interest in the study. To complete this evaluation, we conducted full-text screening and excluded 70 articles due to the unavailability of the required statistics. This also included removing qualitative studies, which were left unscreened in the abstract screening phase. We were left with 67 articles. Finally, we shared a call for unpublished studies on ELMAR and complemented this with an additional search for theses and dissertations on EBSCO and ProQuest to further account for unpublished documents. Through this, we found four additional works, which were included. Finally, 71 articles describing 88 studies and featuring 42,102 unique respondents were selected for inclusion in this meta-analysis (Supporting Information S1: Appendix B).

Two independent experts coded for the variables based on the study descriptions (e.g., the construct definitions and scale items used in the articles). The intercoder agreement was more than 96%, and

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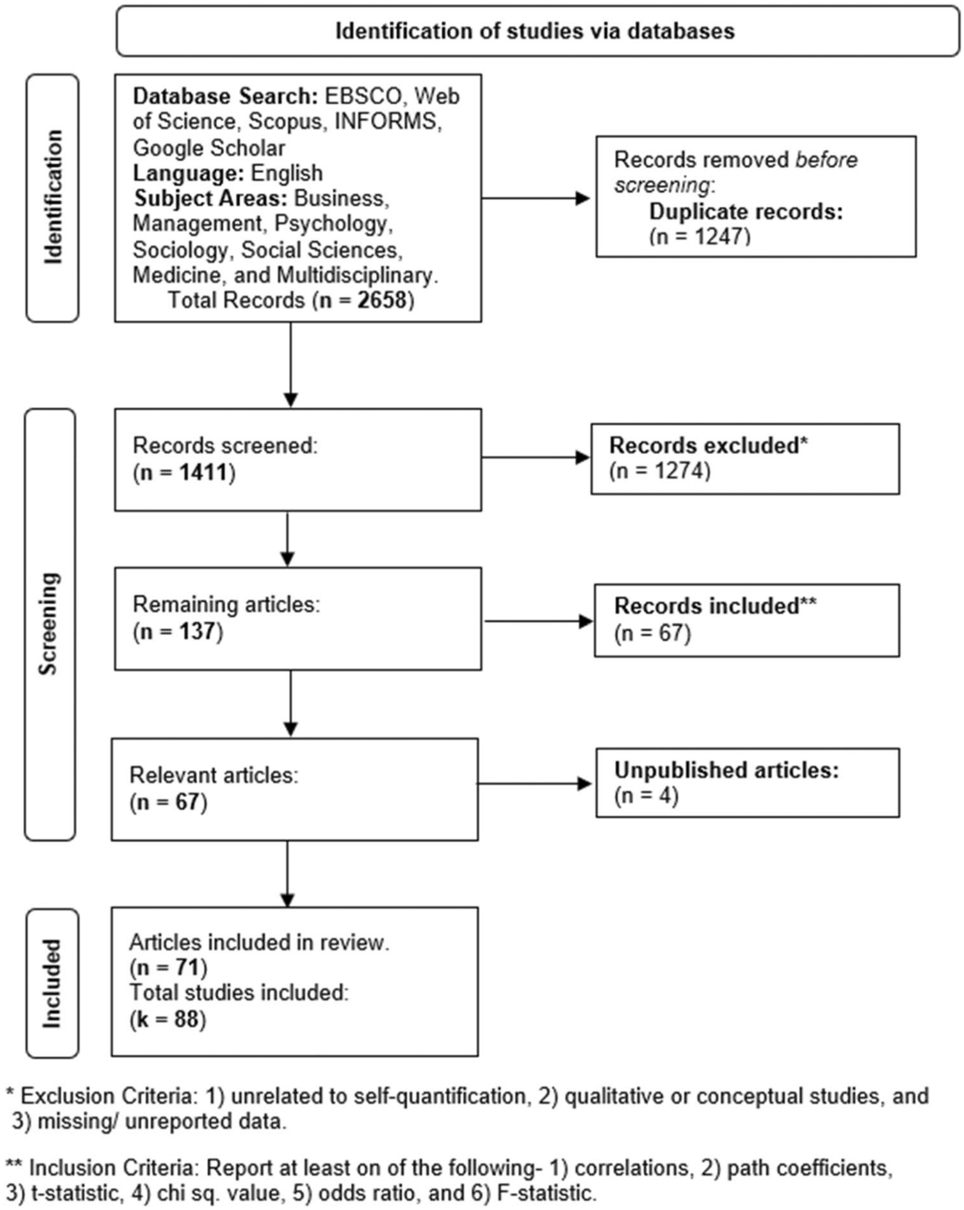

FIGURE 2 Preferred Reporting Items for Systematic reviews and Meta-Analyses (PRISMA) flow diagram illustrating the search protocol.

disagreements were resolved through discussions in the presence of another neutral expert. Table 2 presents the coding scheme for the variables used.

3.2 | Effect size integration and publication bias assessment

We followed the recommendations and procedures followed in meta-analyses that were recently published in reputed marketing journals (for details, see Ashaduzzaman et al., 2023; Blut et al., 2023; Maseeh et al., 2022). We used a reliability-adjusted correlation coefficients to calculate effect sizes (Borenstein, 2009; Harrer et al., 2021). This meta-analysis employed a random effects model in the analysis (Hunter & Schmidt, 2004), and the "esc" package (Lüdecke, 2019) was used for the conversion of different effect sizes into correlations. The formulae used for conversion are provided in Supporting Information S1: Appendix C.

To establish the strength and valence of the effect sizes between consumer well-being and its antecedents, and between self-quantification and its antecedents (as they might also affect consumer well-being), we first calculated the bivariate correlations using a random effects model. Understanding the bivariate correlations among constructs enables us to establish an overall effect size between the constructs. We chose a random effects model over a fixed effects model because the former considers studies' differences in subtle ways, such as based on the samples used and whether control and treatment groups are used, among other contextual factors (Borenstein et al., 2010). Thus, a random effects

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TABLE 2 Variable coding scheme.

Moderators	Operationalization	Coding
Contextual moderators		
Culture (uncertainty avoidance)	Continuous variable (uncertainty-accepting to uncertainty-avoiding culture) based on the country in which the study was conducted, using Hofstede's index	Continuous variable: Hofstede's index
Culture (individualism)	Continuous variable (collectivistic to individualistic culture) based on the country in which the study was conducted, using Hofstede's index	Continuous variable: Hofstede's index
Prior experience	Whether the participants had prior experience with self-quantification devices or apps	Dummy variable: 0 = No; 1 = Yes
Goal setting	Whether there was a goal or target to be achieved by the participants	Dummy variable: 0 = No; 1 = Yes
Indicators tracked	Whether physical or psychological health indicators were tracked	Dummy variable: 0 = Physiological; 1 = Psychological
Data sharing	Whether data was shared with social groups	Dummy variable: 0 = No; 1 = Yes
Method moderators		
Sampling	Whether the sample was a student population	Dummy variable: 0 = Nonstudent; 1 = Student
Research design	Whether the study was survey-based or experiment-based	Dummy variable: 0 = Survey; 1 = Experimental
Study year	The year in which the study was published	Continuous variable: Publication year

model considers not a single true effect size but a distribution of true effect sizes. A distribution of effect sizes suggests heterogeneity among the effect sizes (Harrer et al., 2021).

For the homogeneity test, we used Higgins and Thompson's (2002) I^2 statistic, in which a result greater than 75% is considered as substantial heterogeneity. To address potential publication bias, the authors followed the recommendations of Rosenthal (1979) and calculated the fail-safe N (FSN), where N is the minimum number of null effects required to render the results nonsignificant at $p = 0.05$. For a FSN > $5k + 10$, where k is number of effect sizes, the results can be considered free from publication bias (Rosenthal, 1979).

3.3 | Meta-analytic structural equation modeling

The meta-analysis compiles the bivariate correlations between the variables in the model into a correlation matrix. We dropped the variables for which this information was missing. Specifically, there was an insufficient number of empirical papers examining the relationship between antecedents of self-quantification (e.g., attitude, hedonic motive, privacy risk, social influence, and perceived usefulness) and the mediators under consideration (i.e., body image and self-esteem), which limits testing through MASEM. Therefore, we dropped these antecedents of self-quantification from analysis. We further discuss this in the Limitations and Future Directions section below. We used this correlation matrix as the input for SPSS Amos version 28, to calculate the direct and indirect effects of self-quantification on consumer well-being. We used the harmonic mean instead of the simple mean ($N = 1756$) for the analysis because the former provides conservative estimates and prevents the overestimation of effects (Viswesvaran & Ones, 1995).

3.4 | Moderator analysis

To address the heterogeneity between the effect of self-quantification on consumer well-being, we conducted a meta-regression of the moderators individually and then ran a multiple meta-regression on only the significant moderators (Blut & Wang, 2020; Iyer et al., 2020). We treated the reliability-adjusted correlation coefficients as the dependent variable and the moderator values as independent variables. We tested for the moderation effects only on the relationship between self-quantification and consumer well-being because it was the only relationship with a sufficiently large number of studies (Iyer et al., 2020). The maximum variance inflation factor between the moderators was 1.3094, ruling out the presence of multicollinearity.

In sum, in this meta-analytic review, we first analyzed the bivariate relationships among the constructs of interest to establish an overall effect size. Based on these bivariate correlations, we constructed a correlation matrix that was used to test the structural model and explore the mediation effect between self-quantification and consumer well-being. Additionally, we studied the differential impact of self-quantification on consumer well-being in the presence of multiple contextual and method moderators. In doing so, we contribute to the current understanding of the effect of self-quantification on consumer well-being and explain the inconsistencies in the extant literature.

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4 | RESULTS

4.1 | Bivariate analysis

We used a random effects model to analyze the data. The results indicate a significant positive association between self-quantification and consumer well-being ($r_c = 0.15$, $p < 0.01$), providing preliminary support to H1a. However, the Q-statistic and I^2 statistic (>75%) indicate high heterogeneity among the relationship, warranting moderator analysis. We also find a positive association between self-quantification and body-image ($r_c = 0.51$, $p < 0.01$), along with a significant negative correlation between body image and self-esteem ($r_c = -0.59$, $p < 0.01$). Results further indicate a strong negative association of body image ($r_c = -0.47$, $p < 0.01$) and a strong positive association of self-esteem ($r_c = 0.53$, $p < 0.05$) with consumer well-being. The results suggest that self-quantification, body image, and self-esteem, as discussed, each play a role in fostering consumer well-being.

The results also indicate a significant association between several antecedents of self-quantification—namely, hedonic motive ($r_c = 0.51$, $p < 0.01$), privacy risk ($r_c = -0.39$, $p < 0.01$), social influence ($r_c = 0.25$, $p < 0.01$), and perceived usefulness ($r_c = 0.66$, $p < 0.01$)—with consumer well-being. We also observe a marginally significant correlation between attitude ($r_c = 0.31$, $p < 0.1$) and consumer well-being. These results suggest that the antecedents of self-quantification may also influence consumer well-being. Table 3 illustrates these bivariate relationships.

Moreover, the associations between self-quantification and its antecedents are in line with effect of self-quantification on consumer well-being. Consumer attitude ($r_c = 0.64$, $p < 0.01$), hedonic motive ($r_c = 0.41$, $p < 0.01$), privacy perception ($r_c = 0.26$, $p < 0.05$), social influence ($r_c = 0.38$, $p < 0.01$), and perceived usefulness ($r_c = 0.65$, $p < 0.01$) have a significant positive effect on self-quantification, indicating that these are strong predictors of self-quantification and, hence, may have a positive effect on consumer well-being. As we were limited, due to a lack of studies, in extending our model to include these antecedents, future research should consider testing the effect of these antecedents on consumer well-being. We do, however, provide preliminary evidence that these factors may also contribute to consumer well-being.

Table 3 indicates that the findings do not suffer from publication bias, as the FSN values are above the threshold of 5k + 10 (Rosenthal, 1979, 1986). However, the I^2 values indicate that there is substantial heterogeneity among the relationships, warranting moderator analysis, which is discussed in a subsequent section.

4.2 | Results of MASEM

We used the correlation matrix (see Table 4) to estimate the causal model between self-quantification and consumer well-being. As discussed, we did not include the antecedents of self-quantification in conducting MASEM due to a paucity of empirical research on the relationships between the antecedents of self-quantification and the mediating variables (i.e., body image and self-esteem). Due to the limited empirical research, it was not possible to construct an input correlation matrix containing all the constructs. The results indicate a good fit for the model—that is, $\chi 2 = 22.9144$, root mean residual (RMR) = 0.0343, standardized RMR = 0.0292, goodness of fit index = 0.9936, composite fit index = 0.992, Tucker–Lewis index = 0.952, normed fit index (NFI) = 0.9917, and root mean square error of approximation = 0.1117.

The results of MASEM (see Figure 3) indicate a significant positive direct effect of self-quantification on consumer well-being ($\beta = 0.564$, $p < 0.01$), supporting H1a. We also find a significant positive effect of self-quantification on body image ($\beta = 0.51$, $p < 0.01$), a negative effect of body image on self-esteem ($\beta = -0.59$, $p < 0.01$), and a significant negative effect of body image on consumer well-being ($\beta = -0.4837$, $p < 0.01$). Furthermore, a significant positive effect of self-esteem on consumer well-being ($\beta = 0.48$, $p < 0.01$) is observed. Table 5 shows the direct, indirect, and total effect of self-quantification on consumer well-being. The results indicate that there is a significant positive direct effect (=0.564) of self-quantification on consumer well-being. However, there is a significant negative indirect effect (= −0.3815) of self-quantification on consumer well-being, supporting H2. The total effect (=0.1824) of self-quantification on consumer well-being is positive. These findings suggest that while self-quantification has a positive direct effect on consumer well-being, it also affects body image issues, which, in turn, lowers the self-esteem of consumers. This is tantamount to an indirect negative effect of self-quantification on well-being. The negative indirect effect reduces the overall positive total effect of self-quantification on well-being.

4.3 | Moderator analysis

To address the heterogeneity issue, we performed meta-regression and examined the moderation effect of uncertainty avoidance, individualism, indicators tracked (physiological vs. psychological), goal setting (yes vs. no), prior experience (yes vs. no), data sharing (yes vs. no), research design (survey vs. experiment), sampling (student vs. nonstudent), and year of publication on the relationship between self-quantification and consumer well-being. Our analysis focused on the relationship between self-quantification and consumer well-being because this relationship could meet the threshold of the number of effect sizes ($k > 30$) suggested by Geyskens et al. (2009).

We first ran meta-regression for one moderator at a time. Our findings showed several significant moderation effects. First, both cultural dimensions—uncertainty avoidance ($\beta = -0.0093$, $p = 0.0154$) and individualism ($\beta = -0.0054$, $p = 0.0021$)—are significant. While an uncertainty-avoiding culture strengthens the relationship between self-quantification and well-being, an individualistic society weakens the effect. Hence, H3a and H3b are supported. We find marginal support for prior experience ($\beta = 0.2061$, $p = 0.0612$) and data sharing ($\beta = 0.3639$, $p = 0.0518$), with both strengthening the relationship

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TABLE 3 Bivariate relationships.

	k	N	r_c	z-Value	p-Value	Q-Statistic	I^2	τ^2	FSN
Relationship with consumer well-being									
Self-quantification	31	14578	0.1468**	2.32	0.01	1639.03	98.17%	0.1206	2280
Body image concerns	7	2929	−0.4723***	−5.46	0.000	125.4870	95.22%	0.0535	1467
Self-esteem	3	537	0.5315**	2.03	0.04	92.5525	97.84%	0.3242	113
Attitude	4	701	0.3107*	1.88	0.06	80.6070	96.28%	0.1828	140
Hedonic motive	3	1043	0.5094***	3.82	0.00	29.3472	93.19%	0.0490	393
Privacy risk	3	1129	−0.3948***	−4.65	0.00	19.2298	89.60%	0.0336	192
Social influence	12	6245	0.2538***	3.62	0.00	356.1340	96.91%	0.0639	1355
Perceived usefulness	3	1395	0.6610***	7.43	0.00	24.9497	91.98%	0.0263	948
Relationship with self-quantification									
Attitude	12	3707	0.6445***	5.46	0.00	788.3115	98.60%	0.2367	8877
Hedonic motive	27	6288	0.4091***	4.30	0.00	1428.2532	98.18%	0.2395	13097
Privacy perception	13	5232	0.2559**	2.05	0.04	680.5676	98.24%	0.1591	1140
Social influence	29	19498	0.3813***	7.12	0.00	1061.4301	97.36%	0.0739	16791
Perceived usefulness	23	6840	0.6482***	11.32	0.00	534.6188	95.88%	0.0802	33207
Self-esteem	3	537	−0.3763***	−6.02	0.00	4.0231	50.29%	0.0072	79
Body image concerns	6	2317	0.5146***	5.73	0.00	71.0220	92.96%	0.0410	1196

Note: k = number of studies; N = sample size; r_c = reliability adjusted average correlation; FSN = fail-safe N.
*$p < 0.1$; **$p < 0.05$; ***$p < 0.001$.

TABLE 4 Correlation matrix.

	1	2	3	4
1. Self-quantification	1.00			
2. Body image concerns	0.51	1.00		
3. Self-esteem	−0.38	−0.59	1.00	
4. Consumer well-being	0.15	−0.47	0.53	1.00

Note: Values below the diagonal represent the meta-analytically derived reliability adjusted correlations. We used the harmonic mean for the total sample = 1756.

between self-quantification and well-being. We find partial support for H4 and H7. However, goal setting ($\beta = 0.0818$, $p > 0.05$) and indicators tracked ($\beta = 0.1522$, $p > 0.05$) did not explain any heterogeneity. Thus, H5 and H6 are not supported. Furthermore, as expected in relation to sampling ($\beta = -0.3226$, $p = 0.0061$), a student sample attenuates the effect size between self-quantification and well-being, with nonstudent samples showing larger effect sizes. Thus, H8 is supported. We did not find support for H9, as the interaction effect of research design ($\beta = -0.2215$, $p > 0.05$) is nonsignificant. Year of publication ($\beta = 0.0392$, $p = 0.0469$) significantly accentuates the relationship between self-quantification and well-being. Thus, H10 is supported.

Next, we added moderators stepwise that significantly explained variations in the effect size, starting with the contextual moderators that explained the heterogeneity the most. Table 6 provides a summary of the results of the moderator analysis. We find that together uncertainty avoidance ($\beta = 0.0079$, $p = 0.0127$), prior experience ($\beta = 0.2831$, $p = 0.0558$), data sharing ($\beta = 0.2295$, $p = 0.0276$), and sampling ($\beta = -0.2535$, $p = 0.0305$) account for 55.43% of the heterogeneity across 27 of 31 effect sizes between self-quantification and consumer well-being.

The results suggest that societies with a higher level of uncertainty avoidance display a stronger positive effect of self-quantification on well-being. This means that uncertainty-avoiding societies are better off than uncertainty-accepting societies when they engage in self-quantification. Our meta-analysis demonstrates that prior experience accentuates the relationship between self-quantification and consumer well-being. Last, we find that data sharing also strengthens the relationship between self-quantification and well-being. However, there is no effect between the various indicators tracked and goal setting. Furthermore, the nonstudent sample displays significantly stronger effect sizes for the positive effect of self-quantification on well-being than does the student population. We discuss the implications of these results in the next section.

5 | DISCUSSION

The results of the bivariate and MASEM analyses suggest that self-quantification has an overall positive effect on consumer well-being. However, self-quantification induces body image issues, lowering

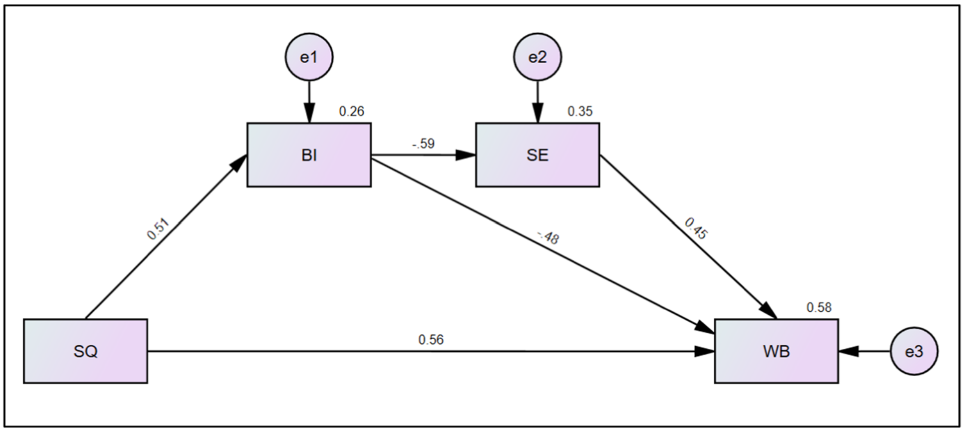

FIGURE 3 MASEM results.

TABLE 5 Direct, indirect, and total effects on consumer well-being.

	Direct	Indirect	Total
Self-quantification	0.564	−0.3815	0.1824
Body image concerns	−0.4837	−0.2645	−0.7481
Self-esteem	0.4482	–	0.4482

self-esteem and, hence, consumer well-being. The MASEM results further provide evidence for the strong direct positive effect of self-quantification on consumer well-being, and the negative indirect effect of self-quantification on consumer well-being via body image and self-esteem. The competitive mediation effect of body image and self-esteem reduces the strength of the overall positive effect of self-quantification on consumer well-being. Furthermore, we find that attitudes toward self-quantification technology, hedonic motive, social influence, and perceived usefulness are positively associated with consumer well-being, while privacy risks are negatively associated with consumer well-being. These results provide preliminary evidence that the antecedents of self-quantification also influence consumer well-being, providing support to our MASEM results, which indicate that self-quantification positively influences consumer well-being. However, due to the limited empirical research available, we were unable to test the structural strength of the relationships between the antecedents of self-quantification and consumer well-being. We recommend that future studies test these effects, as doing so may provide additional insight into consumer well-being. We also find that culture, prior experience, data sharing, and sample characteristics substantially explain the heterogeneity within the relationship between self-quantification and consumer well-being.

We did not find support for the indicators tracked influencing the relationship between self-quantification and consumer well-being. This may be due to consumers tracking multiple indicators simultaneously, as several common self-quantification devices and apps provide information about the whole body (Hoang & Ng, 2023). Moreover, consumers may be using more than one self-quantification device or app to monitor separate indicators, the effect of which is not captured in the meta-data. We did not consider the tracking of both physiological and psychological indicators simultaneously because there is much less empirical research available on the simultaneous tracking of multiple indicators, which limits the inferences that can be drawn via meta-analysis. We urge future scholars to explore the simultaneous tracking of multiple indicators, as this may provide additional insight into its overall effect on consumer well-being.

We also find no conditional effects of goal setting on consumer well-being. The fact that the conditional effects of goal setting did not account for any heterogeneity may be because consumers, irrespective of the researchers providing any goals during the experiment, might have been pursuing their own goals. We believe this to be the case, as the procedures of prior studies did not specifically ask participants not to set or pursue any personal goals during the study period. Therefore, study participants might have been setting their own goals, which might be confounding the effect of goal setting on consumer well-being. Because the previously conducted studies were independent of each other, our assumption that we could control for no goal setting might have been violated, resulting in no significant conditional effect of goal setting on consumer well-being. Future research may address this by conducting lab experiments with specific goal-setting and no-goal-setting conditions. We next discuss the contributions of this study to the theory, followed by recommendations for practice and policy.

5.1 | Theoretical contributions

This meta-analysis contributes to the literature on consumer well-being in the context of self-tracking technologies by providing several key insights. First, it was initially unclear whether self-quantification positively or negatively influences consumer well-being. The meta-analysis proposed and tested a comprehensive framework for consumer well-being in a quantified-self world. The model displays a

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TABLE 6 Moderator results.

Moderator	Intercept	β	SE	p	k	R^2
Uncertainty avoidance	−0.3651	0.0093	0.0036	0.0154	28	21.29%
Individualism	0.5081	−0.0054	0.0021	0.0181	28	20.68%
Prior experience	0.0275	0.2061	0.1057	0.0612	30	12.16%
Indicators tracked	0.0280	0.1522	0.1175	>0.1	27	6.35%
Goal	0.1120	0.0818	0.1540	>0.1	30	0.97%
Data sharing	0.0887	0.3639	0.1791	0.0518	30	12.83%
Sampling	0.2213	−0.3226	0.1090	0.0061	31	23.88%
Research design	0.1921	−0.2215	0.1172	>0.1	31	10.89%
Year	−78.950	0.0392	0.0189	0.0469	31	12.81%
Results of multiple meta-regression						
	β	SE	t-statistic	p	−95%CI	+95%CI
Intercept	−0.3835[b]	0.1947	−1.9697	0.06	−0.7873	0.0203
Uncertainty avoidance	0.0079[a]	0.0029	2.7126	0.01	0.0019	0.0139
Prior experience	0.2831[b]	0.1402	2.0194	0.06	−0.0076	0.5739
Data sharing	0.2295[a]	0.0973	2.3594	0.03	0.0278	0.4313
Sampling	−0.2535[a]	0.1097	−2.3117	0.03	−0.4810	−0.0261

Note: SE = standard error; *k* = number of effect sizes; R^2 = amount of heterogeneity accounted for; CI = confidence interval; VIF = variance inflation factor. For multiple meta-regression, *k* = 27, R^2 = 55.43%, max. VIF = 1.3094, [a]$p < 0.05$, [b]$p < 0.1$.

good fit for the diverse sample under different conditions, providing strong evidence of the validity of the proposed model. The meta-analysis explains the overall effect of self-quantification on consumer well-being, the mediation effect of body image and self-esteem, and the moderating effects on the relationship between self-quantification and consumer well-being; together, these effects substantially explain the mixed findings in the literature. The present study contributes not only to the marketing literature on consumer well-being but also to the information systems (IS) literature on the consequences of self-quantification technology.

Second, we assessed the associations between the antecedents of self-quantification and consumer well-being, as these drivers may also be responsible for consumer well-being. In doing so, we answer the call from Hollebeek and Belk (2021) to explore consumer well-being in a technology context. We provide preliminary empirical evidence that the functional attributes of technology adoption and acceptance models (Davis, Bagozzi, et al., 1989; Venkatesh et al., 2003, 2012) can predict consumer well-being. We observe that the antecedents to self-quantification—namely, attitude, motive, social influence, and perceived usefulness—are positively associated with consumer well-being, while privacy risks and concerns are negatively associated with consumer well-being. These findings suggest that consistent with the technology acceptance model (TAM), the unified theory of acceptance and use of technology (UTAUT), and other technology adoption models, the functional antecedents to self-quantification may also significantly predict consumer well-being. Due to the limited empirical research available in the context of self-quantification, we were unable to test the structural relationships for the same. However, we provide a foundation upon which future scholars can build, and we explore and extend the literature on consumer well-being in technology contexts.

Third, we contribute to the literature on consumer well-being in the self-quantification context by exploring the relationship between self-quantification and consumer well-being through the lens of objectification theory. The extant literature has largely examined the mediation of functional attributes of self-quantification technology (mainly explained by the TAM/UTAUT) in driving continued usage behavior. This prevailing view limits the understanding of consumer well-being in a self-quantification context. Despite literature suggesting the role of self-quantification in enhancing mind–body dualism and self-objectification (see Hoang & Ng, 2023; Peterson Fronczek et al., 2022), there has been little effort to synthesize its effect on consumer well-being. Thus, by exploring the phenomenon of self-quantification from an objectification lens, we direct the focus of scholars toward a new perspective. In the current study, we find that body image and self-esteem mediate the relationship between self-quantification and well-being. The effect is significant and negative. The negative indirect effect of self-quantification reduces the influence of the positive direct effect of self-quantification on consumer well-being. Self-quantification contributes to body image issues among consumers, which in turn reduces self-esteem, causing consumers' well-being to deteriorate.

Last, we contribute to the consumer well-being theory in the context of technology by explaining the reasons for the mixed

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findings in the extant literature by exploring several contextual and study moderators previously unexplored in the literature. The absence of a meta-analysis in the field of self-quantification made the field prone to inconsistencies. We fill this gap by assessing the conditional effects of culture, prior experience, indicator type, goal setting, data sharing, and different study characteristics in explaining the heterogeneity among past findings. The results enrich our understanding of the various conditions, helping to explain the differences observed among studies analyzing the effect of self-quantification on consumer well-being.

5.2 | Managerial and policy implications

With the proliferation of self-quantification devices and apps, it has become imperative for firms to understand whether the products and services commonly marketed as enhancing well-being actually enhance well-being. Moreover, marketers must know the conditions under which these products and services are effective and ineffective. We provide several insights for practice and policymaking, which can be used not only to increase consumer well-being but also to prevent the deterioration of consumer well-being. First, we find that self-quantification has a robust positive effect on well-being. This finding emphasizes that self-quantification will improve consumers' quality of life (Sirgy et al., 2007) by enhancing their well-being. Thus, we recommend that practitioners from various fields—such as medicine, health care, leisure, and recreation, among others—develop products, services, and programs involving self-quantification features. For example, the smartphone game Pokémon GO, which incorporates quantified-self elements, represents an appropriate case for such an innovation. In addition to offering entertainment, the use of self-quantification features in the game encourages users to be active, thereby enhancing and maintaining their well-being. The finding holds significance not only for the manufacturers and service providers of self-quantification technologies but also for policymakers, as such technologies can contribute to UN SDG 3 by promoting well-being among consumers through self-quantification.

However, we recommend that practitioners exercise caution in implementing quantified-self features within their products and services, as it may lead to body image issues among consumers. It is evident that self-quantification increases body image concerns and lowers consumers' self-esteem, which deteriorates their well-being. Specifically, focusing on how their bodies are perceived and internalizing beauty standards can cause body image issues among self-quantifying consumers, subsequently lowering their self-esteem. We could not explore the conditions that might mitigate the negative effects of self-quantification on body image issues due to the limited empirical research available. However, the mere presence of a negative effect emphasizes the need for marketers to be responsible by, for example, running awareness campaigns and providing standard guidelines on when and how to use self-quantification technology. They should also avoid body-related communications in their advertisements. As the present study demonstrates that self-quantification has both positive and negative effects, firms should develop strategies not only to mitigate the negative effects but also to strengthen the positive effects. To achieve this, companies should provide support and resources to help consumers navigate the potential body image challenges associated with self-quantification and promote a healthy and balanced perspective of self-improvement. Policymakers should formulate guidelines according to which the industry and consumers can regulate the use of self-quantification. Additionally, policymakers should introduce legislation to discourage “ideal body” communications. We urge future research to explore the conditions under which the negative effects of self-quantification can be mitigated.

Second, using meta-regression, we assess the moderators influencing the direct relationship between self-quantification and consumer well-being. Our findings reveal that the impact of self-quantification on consumer well-being exhibits greater strength within societies that are characterized by high levels of uncertainty avoidance, such as Finland and Brazil, compared to societies with lower levels of uncertainty avoidance, such as Denmark and Singapore. Additionally, we find that individualistic cultures, such as the USA and Germany, demonstrate a smaller effect of self-quantification on consumer well-being in contrast to collectivistic cultures, such as South Korea and India. These findings suggest that marketers should strategically leverage cultural dimensions to segment markets effectively, employing tailored approaches for disparate cultural segments. For example, our findings indicate a stronger effect of self-quantification on well-being in markets with high uncertainty avoidance and with a collectivistic culture, such as Italy or South Korea. Utilizing this insight in their marketing strategy, firms should market self-quantification devices and apps as a well-being-enhancing offering in such markets. However, this would not be an effective strategy when marketing self-quantification devices and apps in markets with low uncertainty avoidance and with high individualism, such as the USA and Singapore. Instead, marketers could position self-quantification devices as tools for performance enhancement in such cultures. The findings suggest that marketers should devise different strategies for different segments and position their offerings accordingly. Tailoring marketing strategies to accommodate cultural differences—especially for collectivistic and uncertainty-avoiding cultures—could be highly effective. This finding also has implications for policymakers from societies that are uncomfortable with uncertainty and those that expect individuals to be interdependent rather than independent. Policymakers in such countries should consider promoting self-quantification devices and apps to improve the well-being of their citizens.

Third, we find that the sharing of goal progress cues and goal completion information gathered using self-quantification technology on social networks enhances consumer well-being. For firms, this suggests the importance of integrating such design features. Although most of these devices and apps have data sharing features, improving these features and making data sharing among peer groups or on social media platforms seamless will be beneficial for firms.

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Also, brands need to leverage their established online brand communities as a platform on which consumers can actively share their progress. This will have two main benefits: first, it will enhance consumer well-being, and second, it will garner more engagement for firms. Our analysis reveals that prior experience positively moderates the effect of self-quantification on consumer well-being. Firms should highlight the community benefits of social platforms, fostering a healthy competitive environment in brand communities. Based on this finding, marketers should also encourage consumers to be engaged with their self-quantification devices, as experience with devices strengthens the effect of self-quantification on well-being. In this vein, companies should leverage their experienced consumers and incorporate feedback to improve product features and usability. We also found no difference when considering a few contextual moderators such as goal setting and type of indicator tracked. Therefore, firms focusing on self-quantification devices and apps as well-being-enhancing products and services can save resources by limiting research and development related to these factors, as they do not have any conditional effect on consumers' well-being. Rather than relying on a set of indicators or goal setting from consumers to drive consumer well-being, companies should provide multiple options that accommodate individual needs and preferences. Firms should emphasize the versatility and adaptability of self-quantification tools to highlight their ability to support a wide range of tracking indicators and goal setting approaches. This will encourage consumers to track different parameters and set personalized goals based on their circumstances and objectives, which does not deteriorate their well-being. Firms should continuously focus on user experience, irrespective of any specific indicator tracking or goal setting.

Fourth, we identify the factors influencing self-quantification that also affect consumer well-being. We observe that the antecedents of self-quantification—namely, attitude, motive, social influence, and perceived usefulness—are also positively associated with consumer well-being, while privacy risks and concerns are negatively associated with consumer well-being. Marketers may utilize these functional attributes to position their products and services in line with self-quantification drivers. Because privacy risks are negatively associated with self-quantification and consumer well-being, we recommend that marketers take necessary steps, such as providing disclaimers and running awareness campaigns relating to safety and security features. Policymakers can aid in mitigating these concerns by strengthening the existing regulations and running awareness campaigns communicating redressal procedures. Table 7, below, provides an overview of our recommendations to marketers and policymakers.

6 | LIMITATIONS AND FUTURE DIRECTIONS

Although this study provides several valuable insights into the theory, practice, and policy of self-quantification by resolving dilemmas related to mixed findings in the literature and by highlighting various conditional effects, it has some limitations that should be acknowledged. First, our study is limited to only quantitative empirical research in English. Hence, some relevant research, either qualitative in nature or written in other languages, might have been excluded. We were unable to test potential moderators of the indirect effect between self-quantification and consumer well-being due to the limited existing research. Future research should explore factors that can mitigate the adverse effects of self-quantification on well-being. We suggest future researchers examine whether gender and cultural differences alleviate the negative impact of self-quantification on body image. The current literature lacks sufficient empirical studies reflecting gender as a moderator in the self-quantification context. We tested for moderation effects where at least 10 effect sizes were available (Iyer et al., 2020; Samaha et al., 2014). While gender may significantly moderate the relationships between self-quantification, body image, and consumer well-being—given documented variations in body image concerns across genders—we could not meaningfully investigate this relationship due to the lack of a sufficient number of studies. Similarly, cultural dimensions such as individualism and uncertainty avoidance may influence the impact of self-quantification on body image, self-esteem, and well-being. In highly individualistic cultures, where personal achievement and external comparison are emphasized, self-quantification may exacerbate negative body image concerns and lower self-esteem due to societal pressures. Conversely, in cultures with high uncertainty avoidance, structured feedback from self-quantification tools may help manage uncertainty, potentially mitigating negative effects on body image and self-esteem. Although we could not test these moderators due to a lack of a sufficient number of empirical studies, their potential significance is acknowledged. We therefore recommend further research, should consider exploring the roles of these cultural dimensions in greater depth.

We were also limited to testing three effects on consumer well-being using MASEM due to a lack of empirical research on some constructs. However, the model-fit indices and FSN results suggest that this did not hamper the robustness of the model. The model displays a good fit for the data captured by previous studies under different conditions and with different samples, providing strong validity to the model. We further could not test the structural strength of the antecedents to self-quantification on consumer well-being due to the limited empirical research. However, we provide some preliminary evidence of potential relationships that can be explored further in future studies.

In seeking to address the reasons for the mixed findings in the extant literature, this study has explored what we *already* know. The remainder of the section focuses on the existing gaps in the literature and addresses what we *should* know that we *do not* know yet. We thus present some directions for future research, drawing from our study. First, future studies should consider the effects of antecedents to self-quantification on well-being. We find preliminary support for attitude and other motivational and functional antecedents to self-quantification previously described in the literature relating to technology acceptance and use (Davis, 1989; Venkatesh et al., 2012),

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TABLE 7 Managerial and policy implications related to self-quantification (SQ) and well-being (WB).

Key findings	Recommendations for marketers	Recommendations for policymakers
• SQ positively influences WB.	• Practitioners from different fields should consider integrating SQ features into their offerings (e.g., Pokémon GO). • Focus on promoting healthy and balanced self-improvement.	• Policymakers can contribute to SDG 3 by encouraging a healthy lifestyle and promoting WB.
• SQ increases body image issues, which reduces self-esteem and deteriorates WB.	• Avoid any form of body-related communications in advertisements. • Provide resources and support to consumers to help them navigate potential body image issues.	• Legislation and guidelines should be introduced regarding the ideal use of SQ technology.
• Culture moderates the relationship between SQ and WB	• Strategically position brands according to cultural differences (e.g., focus on enhancing WB or on enhancing performance).	• Policymakers from societies with uncertainty-avoiding or collectivistic cultural orientations should promote SQ technology among their populations.
• Prior experience moderates the relationship between SQ and WB.	• Promote continued usage, such as by organizing competitions or implementing other gamification techniques. • Leverage existing users' experience to improve product features.	–
• Data sharing moderates the relationship between SQ and WB.	• Ensure seamless data-sharing features. • There is an opportunity to integrate SQ offerings with brand communities. • Promote community benefits to alleviate any negative effects on WB.	–
• Indicator type and goal setting do not moderate the relationship between SQ and WB.	• Save resources by limiting research and development on these factors. • Diversify offerings to include multiple indicators catering to varying consumer preferences and goals. • Highlight the overall benefits of SQ regardless of the indicators tracked or the users' specific goals.	–
• The antecedents to SQ are also associated with WB.	• Use and enhance the functional attributes of SQ technology when positioning it within the market. • Provide disclaimers regarding privacy and data security.	• Strengthen existing regulation with respect to data security and establish redressal mechanisms.

such as hedonic motive, perceived usefulness, social influence, and privacy risk, all of which impact well-being. We also provide preliminary evidence that these functional attributes influence consumer well-being. Future scholars can build on this and explore these antecedents in different contexts, extending the current theoretical understanding. Also, despite several studies exploring the impact of individual consumer differences on self-quantification, there is a dearth of research on whether, how, and when these consumer traits and predispositions influence consumer well-being in the context of self-quantification. This gap highlights an important area for future exploration, especially regarding individual differences that have an impact on both self-quantification and consumer well-being. It would be interesting to see whether the individual differences that impact self-quantification also influence consumer well-being.

Second, scholars should consider using the theoretical lens of self-objectification. We find a competitive serial mediation effect of body image and self-esteem, which reduces the overall effect of self-quantification on consumer well-being. Scholars can build on this by studying different boundary conditions that can reduce self-quantification's effect on body image or weaken the impact of body image issues on well-being. There is a dearth of studies exploring the boundary conditions regarding what can attenuate the effect of self-quantification on body image, which limited us in studying the moderation effects on the indirect path. Also, it would be interesting to understand the conditions under which self-quantification can enhance self-esteem to improve well-being.

Third, the testing of other novel moderators is extremely important. We tested several moderation effects on the relationship

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between self-quantification and well-being; however, a few moderators were nonsignificant. Scholars should consider testing other novel moderators at an individual level (e.g., locus of control, goal progress cues, and innovativeness). The identification of these novel moderators is one of the key contributions of this study, as it suggests potential new avenues for understanding the roles of individual-level differences in determining the impact of self-quantification. We could not consider individual-level moderators (e.g., attribution style, health, and fitness orientation), which could explain additional variations among the self-quantification consequences. Thus, we recommend that scholars explore additional factors that can influence the relationship between self-quantification and well-being and add to the transformational consumer research.

Fourth, apart from well-being, self-quantification can have other areas of consequence. Scholars should consider the effect of self-quantification on new outcomes. We investigated the effect of self-quantification on consumer well-being, which is an important outcome for transformational consumer research and positive marketing. However, considering the growing interest of consumers and brands in self-quantification, its effect on other consumer-related outcomes (e.g., consumer experience, habit formation, and consumer satisfaction) should also be explored. This aspect expands the theoretical and practical relevance of self-quantification beyond well-being, making a novel contribution to the literature. Self-quantification can be seen as a novel tool to engage consumers while improving their well-being. Therefore, it can also potentially influence brand-related outcomes (e.g., feedback effects and firm performance). Future studies should explore these novel self-quantification effects. Additionally, it would be interesting to investigate unintended consequences of self-quantification, such as obsession or addiction, which remain underexplored in the current literature. As the field of self-quantification continues to evolve with advancements in AI-driven personalization and wearable technologies, future research must explore how these innovations impact consumer well-being, habit formation, and brand-related outcomes. This study provides foundational insights, encouraging future scholars to delve into the technological, social, and ethical considerations of self-quantification as it becomes more integrated into daily consumer behavior.

Last, we recommend that future studies consider diverse research designs. Many surveys and experimental studies have been conducted, with a few longitudinal designs in the context of self-quantification to measure intentions and actual consumer behavior. To build on this, we recommend that scholars explore the real-time data generated by self-quantifying individuals, which would enable a shift from studying consumer intentions to actual behavior over time. This approach could yield novel insights into how self-quantification impacts consumer behavior in the long term. We hope that scholars find these future research directions exciting and that they continue to engage in studying self-quantification behavior.

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CONFLICT OF INTEREST STATEMENT

The authors declare no conflicts of interest.

DATA AVAILABILITY STATEMENT

The data that support the findings of this study are available from the corresponding author upon reasonable request.

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