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How reliable are self-assessments using mobile technology in healthcare? The effects of technology identity and self-efficacy



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ABSTRACT

Traditionally in clinics or hospitals, it is the staff (physician, nurses, and so forth) who would check the patient's health status (e.g., blood pressure, height, weight, body temperature, and so forth). However, when mobile apps are used as the point of contact between patients and healthcare providers, the self-monitoring of health status will be exposed to biases due to being done by common people. Therefore 'self-report reliability' becomes an essential factor in the mobile healthcare context. Drawing on 'technology identity' and 'technology self-efficacy' literature, we theorized that perceived mobile technology identity directly affects self-report reliability, and perceived self-efficacy moderates the relationship between the two. A sample of patients from a clinic who completed a survey and self-reported their health status using a mobile health app was collected. The results of the analyses suggest that academic education affects the reliability of self-reports. In addition, patients aged 61 and above were more accurate in reporting their health status. Moreover, we found that self-efficacy improves the accuracy of self-reports and moderates the effect of mobile technology identity on self-report reliability. The findings of this paper contribute to the ongoing research around mobile healthcare application use and issues surrounding this phenomenon.

1. Introduction

Mobile computing offers fairly cheap and accessible outlets with wide-spread functionalities that are adopted in business and healthcare. In healthcare, especially in the most recent years, mobile devices are used extensively to improve patient life quality and health. Mobile healthcare or m-Healthcare solutions are used in the remote monitoring of patients, delivering care, reducing costs, saving time, and increasing accessibility and geographical coverage of services (Reychav, Kumi, Sabherwal, & Azuri, 2016; Shin, Lee, & Hwang, 2017; Silva, Rodrigues, de la Torre Díez, López-Coronado, & Saleem, 2015). Smartphones are the most publicly available examples of such technology use in healthcare (Petrovič, Rogelj, & Dolničar, 2018). In particular, adoption and use of smartphone healthcare apps can help disabled and elderly people who need extra attention and care.

Traditionally in clinics or hospitals, it is the staff (physician, nurses,

and so forth) who would check the patient's health status (e.g., blood pressure, height, weight, body temperature, and so forth). However, when mobile apps are used as the point of contact between patients and healthcare providers, the self-monitoring of health status will be exposed to biases due to being done by common people (Bardage et al., 2005; Bowring et al., 2012; Froom, Melamed, Tribler, Ratson, & Hermoni, 2004; Gorber, Tremblay, Moher, & Gorber, 2007; Kaplan & Baron-Epel, 2003; Shmueli, 2003; Shmueli, Messika, Murad, & Freedman, 2008; Taylor et al., 2006). Hence, in addition to adoption and commitment interests of patients, the reliability of self-report becomes an important topic that needs to be addressed (Shin et al., 2017).

Self-report, self-monitoring, and self-tracking are similar concepts in healthcare information systems that refer to the individuals' engagement in tracking their own health status by providing inputs to a technological device (Shin & Biocca, 2017). The bias in self-report could be due to: (a) demographic characteristics (i.e., age, gender,

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education); (b) personality traits; (c) physical and mental state of the individual; and (d) environmental factors, one of which is the effect of technology on the individual or the user experience with the technology (Bardage et al., 2005; Baron-Epel, Friedman, & Lernau, 2008; Bowring et al., 2012; Froom et al., 2004; Kaplan & Baron-Epel, 2003). Literature on mobile technology identity (MTI) and self-efficacy (Carter & Grover, 2015; Carter, Grover, & Thatcher, 2013, 2016, pp. 150–164, pp. 1435–1447) suggest that users' ability to identify themselves with mobile technology affects their behavior (i.e., using application features, enhanced use, or resistance behavior), and can therefore affect patients' self-report reliability.

While recent works addressed the factors affecting adoption of self-monitoring devices (Shin & Biocca, 2017; Shin et al., 2017) such as credibility and utility, the purpose of this study is to shed light on the factors that affect reliability of self-report data in healthcare context which can cast a barrier in post-adoption phase of m-Healthcare devices. For example, if users perceive high utility and trust using m-health technologies they will adopt them, however, if their self-monitoring data inputs are biased (unreliable) then the physicians cannot provide effective care remotely as the result of biased records provided by the patients. Against this backdrop, this paper will answer the following research questions:

1. What is the effect of demographic characteristics on the self-report reliability of physical wellness indices such as height, weight, and blood pressure?
2. What is the effect of perceived MTI on the self-report reliability of physical wellness indices?
3. Does perceived self-efficacy moderates the effect of MTI on the self-report reliability of physical wellness indices?

To address these questions, this paper draws on identity theory (Carter & Grover, 2015), self-efficacy (Compeau & Higgins, 1995), and self-report reliability concept in healthcare (Bowring et al., 2012; Thomaz, Silva, & Costa, 2013). Accordingly, a sample of self-reported data collected from patients attending a local clinic. This work will contribute to the growing body of literature on healthcare apps adoption and issues related to the effective use of this advancing technology-enabled services in the healthcare context.

2. Theoretical foundation

2.1. Identification with mobile technology

Identification is an essential tool for the continuity of one's self-perception, enhancing one's ability of self-evaluation (Burke & Stets, 2009). This tool, in effect, creates an ongoing, stable environment for the individual by validating the significance of the organization of personal information and the understanding and response to one's surroundings. This is a very essential component in the life of the individual and leads the individual to participate in activities that verify the identification felt by the individual. Identity Theory explains the influence of the social structure of individuals and its effect on how the individual views him/herself and how one chooses to act within that particular social framework. In that respect, the behavior of the individual is dependent upon the way he/she identifies with different objects in a group, positions, characteristics and more.

According to Carter et al. (2013), people interact with and assign different levels of significance to their mobile phones, but the common denominator is the increase of their self-perception with regard to the device in their possession. The range of perception fluctuates between assigning a functional significance to the device and developing an emotional connection to the device as a sign of self-perception, as described heretofore:

- a. Perception of the mobile device as a functional tool. This perception

answers the question: “What can a mobile phone do for me?” and is characterized by relatively little and not very diversified use of the device. Individuals who identify with this perception view the mobile device as a separate entity and feel that its technical advantages mainly increase capabilities, provide convenience and the feeling of security in certain situations.

- b. Perception of the mobile device as a significant part of one's self-definition. This perception answers the question: “Who am I with regard to my mobile phone?” and is characterized by the diverse use of the device for a wide range of situations and areas of daily life. Individuals who identify with this perception have feelings of relatedness and emotional dependence towards their personal device.

To better comprehend the significance that individuals assign to the incorporation of mobile technology in their daily lives, Carter, Grover and Thatcher (Carter & Grover, 2015; Carter et al., 2013, pp. 150–164) formulated a theoretical model called “Identification with Mobile Technology.” The theory is based upon existing identity theories according to which identity represents the significance and expectations that the individual internalizes and, in turn, can explain his/her behavior (Stets & Biga, 2003). As such, identification with mobile IT technology is the method in which the individual perceives the use of IT technology as an integral part of his/her own self-perception. (Carter & Grover, 2015). The cumulative positive experience that results from comprehensive use of the mobile device encourages the discovery of authentic behavior – the ability of the individual to be true to oneself in a variety of situations (Hillmer, 2009). According to “Identification with Mobile Technology” theory, identity perceived within an environmental context expresses the level at which individuals experience the emotional energy, a feeling of relatedness and dependency when they think about themselves in the context of their environment (Clayton & Opatow, 2003; Stets & Biga, 2003).

2.1.1. Emotional energy

Emotional energy is defined as the level at which the individual expresses continuous feelings of security, energy, and excitement when using IT technology as a result of positive interactions in the past. Feelings of emotional security emerge when the individual thinks about himself in conjunction with his mobile phone. For example: “The phone is a means to inform and empower us. You take control by not giving in to something that is not ideal. It can be something as simple as avoiding traffic or checking the price of an item at different stores. Either way, you have the power and the control Your self-esteem is then fuelled by that power, so you feel more secure.” (Carter et al., 2016, p. 1438) Studies focusing on identity make note of interactions that develop between people and objects (in conjunction with the interaction between individuals) and the impact they make on thought and behavioral patterns. These types of interactions can hold more emotional and ideological impact on certain people than others (Clayton & Opatow, 2003). Therefore, it is important to check the level at which the mobile phone becomes an integral part of an individual's self-perception and behavioral patterns, especially among teens and young adults who show feelings of enthusiasm and security when they think about themselves with regard to their mobile phones. The absence of the device leaves these people uncomfortable and limits their ability to perform daily tasks. One explanation for those feelings is that the mobile device carries detailed personal information, memories, and documentation of emotions that relate to the individual's prior interactions with the device (Vincent, 2006). So, individuals may experience the absence of the device as the loss of an important part of themselves. Individuals with high emotional energy feel more enthusiastic when the device is returned to them (Carter et al., 2016, pp. 1435–1447).

2.1.2. Relatedness

The feeling of relatedness to mobile technology represents the obscure boundary between the self and technological means. This can be

defined as the level on which the individual expresses feelings of connection or a close and significant relationship when thinking of his/herself with regard to his/her personal mobile device. For example: “My mobile phone is so integrated into my life that without my phone I feel as though I am no one, lost on this earth.” (Carter et al., 2016, p. 1438) Studies that focus on identity perception define relatedness as the most sought-after component of the perception of personal identity (Clayton & Opatow, 2003). A study by Carter et al. (2013, pp. 150–164) shows that the feeling of relatedness of individuals to their mobile devices is influenced by the significance that they assign to the use of the device. Studies show that people who report all of the actions that they can perform via their device show much lower levels of relatedness to their device than people who define the importance of the device as their means of connection with their surroundings. Loss of the device for people with a high level of relatedness to their device is experienced as an extreme and powerful detachment from their surroundings.

When an individual feels a physical or emotional advantage by using a certain technology, the individual develops a stronger feeling of relatedness towards that medium and increases his/her tendency to use it for other purposes as well (Bhattacharjee & Premkumar, 2004; Carter & Grover, 2015; Venkatesh & Bala, 2008). Studies that focus upon the process of technology adoption (Davis, 1985, 1989; Mao, Srite, Thatcher, & Yaprak, 2005) show that the tendency to maximize options offered by a specific form of technology is influenced by the relationship of the individual towards that form of technology, the level of his/her trust and perception of its efficacy. The level of perceived ease of use is also a significant factor in determining its perceived efficacy for various needs.

2.1.3. Dependence

A feeling of emotional dependence on mobile IT technology in general, and on one's personal device specifically, is defined by the level at which the individual expresses feelings of great need for the device, and relies upon it when thinking about him/herself with regard to the device, assuming, of course, that mobile technology is available at all times and all places. For example: “The one day of not having my phone available for use made me realize how dependent I have become on it My phone is like a lifeline to me.” (Carter et al., 2016, p. 1438) In addition, feelings of great relatedness to any object are directly connected to the development of a feeling of dependence towards the object. Indeed, both concepts – relatedness and dependence – are noted in the professional literature that deals with the relationship towards inanimate objects as part of one's identity perception (Clayton & Opatow, 2003).

Carter et al. (2013) claimed that the more the use of the mobile device is incorporated into daily life, so too, the more the individual becomes more dependent on the device, especially when pursuing and strengthening social relationships, work-related issues, leisure and fun (Carter et al., 2016, pp. 1435–1447). In addition, the study showed that young adults perceive their dependence on the mobile device in different manners: Those who perceive the device as a functional tool report that in its absence (due to loss or malfunction), they feel a loss of convenience that the device offers them. On the other hand, those who perceive the device as a significant factor in their self-perception expressed strong feelings of dependence towards their device, including emotional tension, fear, anxiety, and panic. When asked to describe a scenario of their future without the device, participants became very insecure and vulnerable.

2.2. Quantified self and self-reporting personal health-related data

The current state of technology allows healthcare professionals, experts, and regulators to shift some part of the care delivery toward patients, this has led to the emergence of “Quantified Self” communities and social networks (Gimpel & Niben, 2013). The quantified self movement uses apps, smartphones, computers, wearable devices and a like to help patients self-track, self-monitor, or self-report their physical

health status that is used by physicians to diagnose patient conditions (Wang, Weber, & Mitra, 2016). Recent works such as Shin and Biocca (2017) studied the factors that affect adoption of quantified self interface and they concluded that the factors like perceived utility, hedonicity, expectation confirmation affect users' intention to continue using them. Similarly Shin et al. (2017) studied the credibility and utility of health care information system from users' perspective which affects its continued adoption.

A stream of healthcare literature has examined the role of reliability of data inputs by patients in self-tracking, self-monitoring, and self-reporting conditions that is still relevant in healthcare quantified self movement. National and global programs and studies attempt to cope with the prevalence of overweight and obesity in developed countries; studies that focus on behavioral science and IT systems aim to assess the willingness of individuals to submit self-reports about their weight and height to health systems and then measure the reliability of these reports (Bardage et al., 2005; Bowring et al., 2012; Gorber et al., 2007; Shmueli et al., 2008; Thomaz et al., 2013). Studying self-report reliability has several implications for practice, one of which is improving the quality of experience in user acceptance (Shin & Hwang, 2017).

Prior studies have examined the relationship between personality traits and the reliability of health-related self-reports by adults. These traits include demographic characteristics (age, gender, education, income, etc.; Bardage et al., 2005; Bowring et al., 2012; Froom et al., 2004; Gorber et al., 2007; Kaplan & Baron-Epel, 2003; Shmueli, 2003; Shmueli et al., 2008; Taylor et al., 2006), and traits connected to physical and mental health, such as daily physical exercise, smoking habits, blood pressure, excess weight, diabetes and more. Mental crises, high-pressured life events, lack of social support or feelings of loneliness could also have impact on one's state of health and the reliability of the self-report (Bardage et al., 2005; Baron-Epel et al., 2008; Bowring et al., 2012; Froom et al., 2004; Kaplan & Baron-Epel, 2003). In most cases, the variables of gender and age proved to be the main factors that explained the differences between the reliability of self-reporting in various countries around the world. Engstrom and others (2003) reviewed 35 articles written from 1970 to 2002 that discuss the reliability of self-report of weight and height among women from eleven different countries. Results indicated that in most studies, women tended to overestimate their height and underestimate their weight in their self-reports.

A study in Australia (Bowring et al., 2012) examined whether young adults (aged 16–26) are willing to report their own height and weight, and then measured the reliability of those self-reports. Results showed that 82% of the men and 72% of the women were willing to report their weight and height. The reliability of the reports was assessed among a small sampling of participants who agreed to the review ($n = 67$), and results showed that women tended to report a lower weight than actually recorded, as compared to men. Moreover, young adults were willing to submit self-reports about their height and weight, and those reports were generally reliable. The gender variable remains a factor that explains the differences in the reliability of the reports.

Another study, conducted in Canada (Gorber et al., 2007) on adults (age 18 or above), found significant difference between men and women with regard to the reliability of self-report concerning height and weight but no significant difference between the two groups with regard to the extent of the effect. Moreover, another study, conducted in Australia (Taylor et al., 2006) on adults (age 18 or above) showed that the age explains the varied levels of reliability in the self-report of height. This study showed that adults aged 65 and above had a tendency to report lower values of height than actually measured. However, no significantly defined statistical relationship between age and reliability of self-reporting was noted with regard to reports of weight.

Results of a study in Brazil (Thomaz et al., 2013) that included children and adults showed that the interaction between gender and age had an impact upon the reliability of reporting with regard to height. Men over the age of 60 and girls younger than the age of 12

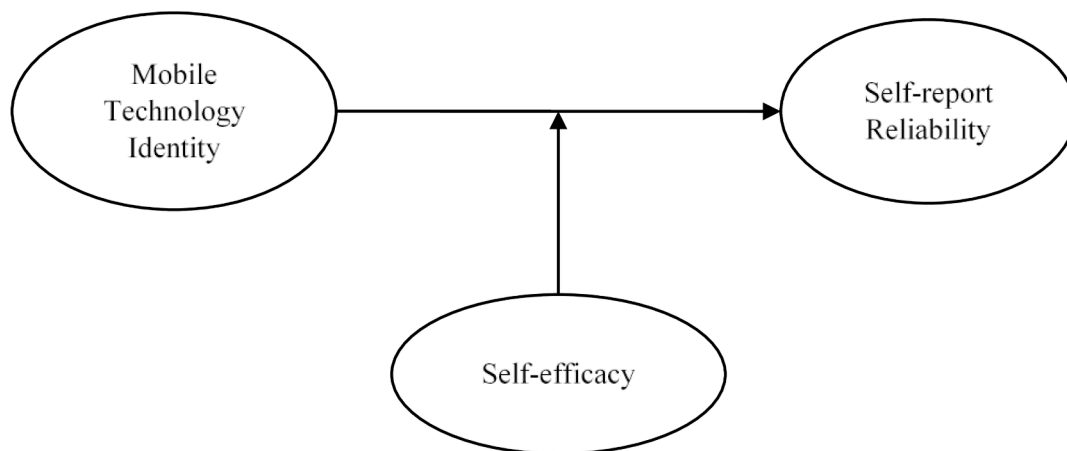


Fig. 1. Research model.

tended to over-estimate and report a higher value for height than actually measured. The range of deviation was set at a relatively broad range (up to 4 kg deviation for weight, and between 4 and 6 cm deviations for height). Even so, no significantly defined statistical differences were noted between the self-reports of body mass measurements (BMI). The study concluded that self-report of height is reliable for groups of women over the age of 12 and groups of men under the age of 60. Self-report of weight was found to be reliable among all participants in the study.

The method of individual information gathering via self-report varies and includes self-report at the health clinic, response to a questionnaire, or a report by phone (Julius, 1991). In the past, self-report data were collected via printed questionnaires or telephone surveys (Tripepi, Jager, Dekker, & Zoccali, 2010; Van Gelder & Pijpe, 2013). Also, internet use creates an additional distance between the interviewer and the participant and provides anonymity that enables the participant to answer personal questions with honesty and offer personal information with greater ease (Joinson, 2001). This distance that increases the response parallels the distance that is created when the participant replies to a questionnaire independently, as was noted with regard to emotional or stigmatic behaviors (Couper, 2000). Along similar lines, Bonn, Lagerros, and Blter (2013) found that the validity of internet-based questionnaires was identical to the validity of printed questionnaires. Moreover, the level of compliance in self-reports of measurements in questionnaires was identical to the level of compliance ($p < 0.001$) in online questionnaires (Bonn, Lagerros, & Blter, 2013).

A large number of studies attempted to check the reliability of information gathered via self-reporting but most focused on a single index, as submitted to a specific staff member or via a single instance of information gathering; some of the studies also focused on self-reports of the medical team. These studies showed that the level of precision of self-reporting varies. The level of precision was high in general, with a high correlation between actual measurements and those reported by patients on questionnaires that were distributed and then collected on an individual basis, but other studies showed a lower correlation when the information was gathered on an individual basis by a member of the medical staff. (Brener, Mcmanus, Galuska, Lowry, & Wechsler, 2003; McAdams, Dam, & Hu, 2007; Niedhammer et al., 2000; Paulet & Rajpura, 2016).

2.3. Self-efficacy

Self-efficacy refers to one's judgments of his/her capabilities to organize and execute courses of action required to attain designated types of performance (Bandura, 1986). Self-efficacy contributes to the users' attitudes and perceptions toward adoption behaviors and more

importantly effective use of IT. Self-efficacy is a central factor in the m-Health engagement of the smartphone app users. In fact, it has been theorized in studies related to effective use of m-Health (Asimakopoulos, Asimakopoulos, & Spillers, 2017). For example, in a recent study by Zhang et al. (2017) they showed that computer self-efficacy positively moderates the effect of perceived usefulness on adoption intention of the m-Health users. In addition, they showed self-efficacy directly affects users' attitude about the introduced technology 'being easy to use'. Likewise, we adopted this construct that we deemed to be an important moderator of self-report reliability.

3. Hypotheses

In this section, we advance our argument regarding the effect of demographic characteristics on the self-report reliability of personal health indices through m-Health apps. Further, we construct our hypotheses and theoretical model based on "self-report reliability" concept, "MTI", and "self-efficacy." In short, we propose that MTI is the main predictor of self-report reliability (in other words, individuals' ability to identify themselves with mobile technology or see it as part of their social identity makes them less biased in their self-report), while self-efficacy moderates this relationship. Fig. 1 summarizes the proposed theoretical model.

Self-report reliability: Individuals differ in the reliability of their self-reports. The difference is due to demographic factors, personality traits, physical and mental conditions (Baron-Epel et al., 2008; Bowring et al., 2012). Age and gender have been consistently found to affect self-report reliabilities. For example, women tend to overestimate their height and weight. Age is another source of bias in self-report reliabilities. Elderly people tend to underestimate or overestimate their heights and weights (Taylor et al., 2006; Thomaz et al., 2013). Psychologically people do not like to associate themselves with things that are considered negative by the public such as obesity. Therefore, they will misread or misreport themselves. Women are more sensitive to own weight and height, and so have a greater tendency to overestimate or underestimate them. In addition, highly educated people, specifically those who were exposed to technology during education, are expected to be more accurate in their self-reports. Hence, we posit:

H1. Demographic characteristics, specifically: (a) age; (b) gender; and (c) education affect the self-report reliability of physical wellness status.

Emotional energy, as a dimension of identity, makes the user enthusiastic, confident, inspired, and excited about the IT device (Carter, 2012). This motivation and the level of engagement that the user experiences when working with a mobile device makes them less prone toward making mistakes when working with their smartphones (Asimakopoulos et al., 2017). If we consider a mobile app as a feature

that comes with smartphones, the use of these technological features is one of the three predicted consequences of mobile identity (Carter & Grover, 2015). When users of m-Health apps know the use of these apps will improve their health condition they will be inspired to use it more often and with care (attention). Hence, they will use it with a high level of positive emotional energy. Accordingly, High levels of positive emotional energy will result in fewer mistakes in self-reports. In fact, there is an extensive body of literature which shows low levels of emotional energy causes boredom which results in poor performance, negligence, and lack of concentration all of which introduces bias in self-reports (Drory, 1982; Watt & Hargis, 2010).

The relatedness dimension which discussed by IT identity model is also part of psychological needs of human per Self-Determination Theory (Ryan & Deci, 2000). When users become integrated, synced, coordinated with their IT devices (i.e. digital blood pressure device) as a direct consequence of frequent use, they master their interactions with it which makes them less prone to making mistakes in measuring and reporting their own physical wellness measures. The identity theory as a lens, explains the learning curve of the user when interacting with IT under the umbrella of relatedness. In particular, Carter (2012), recognized adoption, learning, and exploratory behaviors as the likely outcomes of having a strong IT identity. The learning curve implies that the more time individuals spend on doing a task (like using a mobile app over and over again) they become more efficient and effective (Bailey, 1989). In other words, they become faster and make fewer mistakes when using the app, this is the direct consequence of becoming integrated and synced (relational aspect of identity theory) with the IT device. Thus, higher levels of identification with m-Health apps result in less self-report bias.

Along the same line, being highly dependent on mobile apps for receiving healthcare services makes the users careful in their physical wellbeing assessments and reports because users are aware that the information they provide to the m-Health app has implications on their treatment. The dependence is the result of the individual's "need" on the app (Carter & Grover, 2015; Carter, 2012). Dependence and engagement are positively correlated, so increase in dependence on technology will result in an increase in engagement (Fan, Liu, Wang, & Wang, 2017). User engagement with m-Health app is in the form of giving inputs and receiving outputs on a regular basis. Due to learning curve and experience, higher engagement as well as dependence on an important app which affects the individual health influences the individuals' tendency to pay more attention when self-reporting their physical wellness indices. Consequently, an increase in MTI as a whole will have the same effect on self-reports as each dimension of IT identity. So, we posit:

H2. Perceived MTI positively increases the self-report reliability of physical wellness status.

Self-efficacy: Higher perceived computer self-efficacy increase the self-identification with IT. On the other hand, low levels of computer self-efficacy causes individuals to view themselves independent and separate from technology (Carter, 2012). Low self-efficacy disrupts the individual's compatibility with technology (Wu, Wang, & Lin, 2007). As a result, individual's intention to use the m-Health app for self-reporting is reduced. Even if they do, it will be arbitrary to use these apps; and the user will not engage appropriately to pay enough attention to details while submitting self-reports. Hence, self-efficacy positively affects both MTI and self-report reliability. Nonetheless, self-efficacy will moderate the relationship between MTI and self-report reliability. By extension, higher levels of self-efficacy will exponentially affect the strength of the relationship between MTI and self-report reliability. Furthermore, it is important to mention that conceptually moderations affect the strength of relationship between independent and dependent variable, and based on the literature, computer self-efficacy is one of the main three factors alongside the (a) embeddedness of IT, and (b) actualized reward that increase the strength of IT identity (Carter & Grover, 2015). So, we

hypothesized that:

H3. Higher levels of perceived self-efficacy increase the strength of the relationship between MTI and self-report reliability of physical wellness status.

4. Methods and data

The participants in this study were adults who come for health care at one of the main branches of the National Health Fund clinic in the center of Israel. The participants used smartphones to report their height, weight, systolic blood pressure, and diabolic blood pressure and they were asked to complete an online questionnaire via a mobile device (tablet or mobile phone). The questionnaires were filled out while the participants were waiting in the health clinic's waiting room during their visit to the clinic. The introduction to the questionnaire explains that the study focuses on the use of mobile technology for health-related data and that participation in the study at the health clinic will be conducted only upon patient consent. Participants were assured that their participation would not have any influence on their treatment. The distribution of the questionnaire and the measurements were conducted at the health clinic by a research team of nurses who received appropriate training and were authorized by the management of the healthcare provider and the administration of the branch in which the study took place. In addition, the branch employees and medical staff were given an explanation about the study and its objectives.

Two hundred ninety-two subjects participated in the study of which 220 reported their heights, 244 reported their weights, 104 reported their systolic blood pressure, and 102 reported diastolic blood pressure (for the SEM model per section 5.3 and 5.4 we excluded 25 participants who did not report any of the aforementioned physical health indices). 65 percent of the participants were male. 45 percent hold a non-academic degree. Age-wise, 24 percent were between 18 and 30 year-old, about 49 percent were between 31 and 60 year-old, and 27 percent were 61+ year-old.

4.1. Measures

We conducted the analysis using STATA/IC 15.1 for Windows. In order to test the first hypothesis, we used ANOVA, but for second and third hypotheses we used SEM. The survey construct includes the three dimensions of perceived MTI (based on Carter & Grover, 2015; Carter et al., 2013, pp. 150–164). We used four items for each dimension of perceived MTI. The four items for perceived self-efficacy adapted from Davis (1985) and Liao, Palvia, and Chen (2009). Additionally, some demographic questions, as well as background experience questions about the extent use of health apps, were added to the survey to be used as control variables in the study. The constructs were measured along a five-point Likert scale (1 = Strongly agree; 2 = Agree; 3 = Neutral; 4 = Disagree; 5 = Strongly disagree). The original items are available in Appendix.

4.2. Dependent variable

The dependent variable in this study is self-report reliability, which we estimated using the difference between the self-report through mobile and clinical measures of weight, height, systolic blood pressure, and diabolic blood pressure. Given that the scale of height, weight, and blood pressure are different, we first standardized variables before summing them up (converted them using standardized transformation to bring them to the similar scale with a standard deviation of one). Furthermore, in order to capture biases from all four variables we summated their absolute values in order to reflect the true bias of self-reports. For example, if the standardized height is -1 unit and standardized weight is $+1$ unit the sum of the two will show that there is no bias in the self-reports for that specific individual. However, in reality,

the individual had a bias in both estimations of his height and weight. Therefore, using absolute values will reflect the biases from each variable. Thus, the higher self-report bias, the lower self-report reliability and vice-versa.

$$\text{Self report bias} = \sum ((|Height_{Std}| + |Weight_{Std}| + |Systolic_{Std}| + |Diastolic_{Std}|))$$

5. Analyses and results

5.1. ANOVA

In order to test H1, we conducted ANOVA test on height, weight, and blood pressure report bias with age, education, and gender as the factors. The results of ANOVA on 'self-report bias' did not show any difference between the means of the factors, but the result of individual measure biases (weight bias, height bias, and blood pressure bias) on factors showed some differences. The ANOVA results indicate a significant difference between the means score of *Height bias* for participants with academic degree and participants with non-academic degree ($\mu_{\text{Academic}} = 0.536$; $\mu_{\text{Non-academic}} = 0.738$; $F = 3.67$; $p < 0.057$). The results indicate a similar pattern for *Weight bias* for academic and non-academic ($\mu_{\text{Academic}} = 0.526$; $\mu_{\text{Non-academic}} = 0.721$; $F = 3.78$; $p < 0.053$). Lastly, the results indicate a significant difference in means scores of *Systolic blood pressure bias* for participants aged 31–60 and 18–30 ($\mu_{31-60} = 0.874$; $\mu_{18-30} = 0.483$; $t = 1.89$; $p < 0.061$), and those aged 61+ and 31–60 ($\mu_{61+} = 0.612$; $\mu_{31-60} = 0.874$; $t = -1.87$; $p < 0.064$). However, we did not find a significant difference based on gender, i.e., between men and women in terms of *Height bias*, *Weight bias*, and *Systolic blood pressure bias*. Table 1 provides the complete ANOVA results.

5.2. Survey analysis

The constructs were tested for reliability and validity. The

Table 1
ANOVA results.

Dependent variable	Independent variable	MSB	df	MSE	F	Sig.
Height bias	Education	2.209	(1, 217)	0.602	3.67	0.06
Weight bias	Education	2.300	(1, 241)	0.610	3.78	0.05
Systolic blood pressure bias	Education	0.085	(1, 102)	0.455	0.19	0.66
Diastolic blood pressure bias	Education	0.060	(1, 100)	0.480	0.13	0.72
Height bias	Gender	0.423	(1, 218)	0.608	0.70	0.40
Weight bias	Gender	1.647	(1, 242)	0.610	2.70	0.10
Systolic blood pressure bias	Gender	0.524	(1, 102)	0.450	1.16	0.28
Diastolic blood pressure bias	Gender	0.671	(1, 100)	0.473	1.42	0.23
Height bias	Age	0.339	(1, 139)	0.347	0.98	0.32
18-30 vs 31-60		0.545	(1, 105)	0.471	1.15	0.28
18-30 vs 61+		0.061	(1, 168)	0.463	0.13	0.71
Weight bias	Age	0.148	(1, 161)	0.609	0.24	0.62
18-30 vs 31-60		0.123	(1, 119)	0.600	0.21	0.65
18-30 vs 61+		0.711	(1, 178)	0.626	1.13	0.28
Systolic blood pressure bias	Age	1.530	(1, 55)	0.500	3.04	0.09
18-30 vs 31-60		0.170	(1, 54)	0.300	0.55	0.46
18-30 vs 61+		1.492	(1, 85)	0.457	3.26	0.07
Diastolic blood pressure bias	Age	0.092	(1, 54)	0.336	0.27	0.60
18-30 vs 31-60		0.068	(1, 52)	0.068	0.10	0.75
18-30 vs 61+		0.003	(1, 84)	0.493	0.01	0.93

Cronbach's alpha for Dependence, Emotional Energy, and Self-efficacy were above the suggested value of 0.70 (Hair, Anderson, Tatham, & Black, 2006). However, we excluded Relatedness dimension of identity due to reliability and validity issues. Also, one item each from Dependence, Emotional Energy, and Self-efficacy was removed due to low loadings (Hair et al., 2006) in the confirmatory factor analysis (leaving each construct with three items). The principal component analysis showed that all the three retained items for the three aforementioned constructs are loading highly (above 0.40) on their reciprocal factor.

We conducted two tests to check whether common method variance is an issue (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003). First, employed *Harmon's one-factor test*: This was done by allowing all items to load on a single factor. The result suggested that the single factor only explains 43 percent of the total variance. Given that this is under 50 percent there is no common method bias issue with the sample. Next, we tested *common latent factor* in conjunction with measurement model by adding an artificial construct called *Common Factor* and fixing its variance to 'one' and then adding paths from this construct to all observed variables in the model and fixing the regression weights for these paths to be equal. The result showed that the estimated fixed beta coefficient from Common Factor construct to each observed variable is almost zero (4.08×10^{-08}) and the squared value of this regression weights shows "Common Variance" which is a small number (1.66×10^{-15}). Thus, the common variance was not an issue in our sample.

5.3. Measurement model

The measurement model was assessed using the fit indices recommended by the prior literature (Fornell & Larcker, 1981; Hair et al., 2006; Hu & Bentler, 1999): RMSEA (Root mean squared error of approximation) = 0.056; CFI (Comparative fit index) = 0.978; TLI (Tucker-Lewis index) = 0.967; SRMR (Standardized root mean squared residual) = 0.041; $\chi^2/\text{degree of freedom} = 43.902$ (d.f. = 24; $p < 0.008$), all of which are satisfactory. CFI and TLI are above 0.90; RMSEA and SRMR are under 0.08. Table 1 represents the inter-construct correlations and the average variance extracted (AVE) for the structural model. Per table, convergent and discriminant validity requirements are met. All AVE's are above 0.5, and the square root of AVE exceeds all the correlations between constructs and variables (Fornell & Larcker, 1981). The diagonal of Table 2 lists the square root of AVE's and other cells represent the correlations.

5.4. Structural model

Fig. 2 Summarizes the analysis and results for the structural model. There are several techniques for estimating the interaction effect of latent constructs. Cortina, Chen, and Dunlap (2001) reviewed a few techniques of which Ping (1995) is a well-known method that generates

Table 2
Descriptive statistics, convergent validity, and discriminant validity.

	Convergent validity				Discriminant validity: correlations		
	Mean	St.d.	CR	AVE	1	2	3
1. Mobile technology identity	3.14	0.95	0.83	0.71	0.84		
2. Self-efficacy	3.84	1.07	0.83	0.63	0.40*	0.79	
3. Self-report Bias	2.53	1.49	–	–	0.11	–0.08	1.00

* $p < 0.05$.

St.d. = Standard deviation; CR = Composite Reliability; AVE = Average Variance Extracted.

The diagonal of the matrix shows the square root of AVEs. Since self-report bias is an observed variable the AVE was set to 1.00 for this variable.

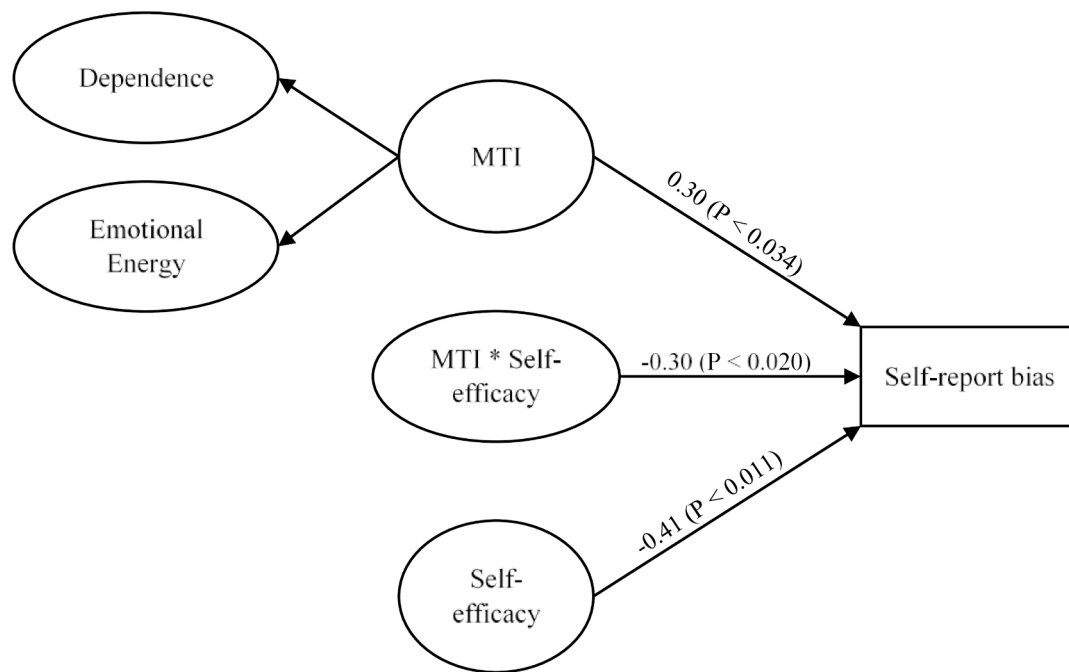


Fig. 2. Results of SEM model.

a single item for the interaction effect and retains all items for the constructs. However, we adopted Lin, Wen, Marsh, and Lin (2010) which is a more recent technique for estimation of interaction latent constructs. This technique that is known as “Double mean centering”, so we mean centered all the items associated with MTI and Self-efficacy then we created interactions of observed variables by multiplying each Self-efficacy item in the reciprocal Dependence and Emotional Energy item which generated six items (three times two) for the interaction latent construct.¹ Next, we mean centered the six generated observed variables for the interaction latent construct.

The baseline model was evaluated by ‘maximum likelihood with missing values’ option and direct and interaction effect without including any control variables. The dependent variable (see section 4.2) had a few missing values thus using maximum likelihood with missing values allowed SEM to substitute for the missing values and converge the model. The fit indices² for the baseline model is as follows: RMSEA = 0.069; CFI = 0.909; TLI = 0.887; $\chi^2/\text{degree of freedom} = 221.952$ (d.f. = 97; $p < 0.001$). We improved the model by allowing covariance between a few error terms per suggested “Modification Indices” (Sabherwal, Jeyaraj, & Chowa, 2006). The fit indices for the final structure model is as follows: RMSEA = 0.049; CFI = 0.957; TLI = 0.944; $\chi^2/\text{degree of freedom} = 150.308$ (d.f. = 92; $p < 0.001$). All indices are above the accepted thresholds. Further, we accounted for the effect of control variables by executing competing models in which education, gender, age, frequency use of healthcare app, and user prior experience with m-Health app were included in the model as control variables. Surprisingly, none of the control variables were significant with the presence of latent variables, and the improvements in fit indices were marginal compared to the final model without any control variable (Fig. 2).

5.5. Results

As shown previously, the final results conclude that some of the

demographic factors affect self-report reliability. As a reminder, the higher the bias score, the lower the reliability and vice versa. The *Weight-* and *Height-bias* scores for people holding academic degree are significantly lower than the *Weight-* and *Height-bias* scores for people without an academic degree. Thus, participants with an academic degree are more accurate in their self-reports. In fact, academic institutions are increasingly doing a better job of introducing the technology to students. Contemporary research case studies show that universities actively integrate technology into their education routines, thus individuals who received academic education are more familiar with technology (Bates, 2000). Moreover, educated individuals are better trained in analytical skills by having math and statistical courses, increasing their ability to measure their height and weight accurately. Lastly, individuals holding academic degree have a better understanding of health risks, so they are more motivated to accurately report themselves (Ross & Wu, 1995).

The results showed that participants aged 31–60 scored higher in *Systolic blood pressure bias* compared to those aged 18–30 ($p < 0.061$); and participants aged 61 and more scored lower in *Systolic blood pressure bias* compared to those aged 31–60. Thus, elderly and young people are more precise in reporting their *Systolic blood pressure*. Since elderly people's treatment is very dependent on these measures so they do their best to be precise in measuring and reporting their blood pressure, and young peoples are millennial's who are very good at using technology especially digital blood pressure devices that are frequently in use are more prone to measure and report precisely. Overall, H1 is supported since we found that all three demographical characteristics (age, gender, and education) have an effect on the self-report reliability of physical wellness status (height, weight, and systolic blood pressure).

The results of the SEM model shows that all path coefficients for direct effects and moderation effect are significant. Specifically, it shows that self-efficacy is negatively associated with self-report bias ($\beta = -0.41$; $p < 0.011$). That means individuals with higher levels of perceived self-efficacy have a lower self-report bias, as a result, their self-report is more reliable. This is consistent with prior works that stated self-efficacy will engage the users and as a result, they will perform better (Wu et al., 2007). However, to our surprise, the direct effect of perceived MTI on self-report bias was positive and significant ($\beta = 0.30$; $p < 0.034$) which means that individuals who highly

¹ The six items for “Mobile tech identity $\times$ Self-efficacy” are generated as the results of reciprocal multiplication of “Self-efficacy $\times$ Dependence” and “Self-efficacy $\times$ Emotional Energy”.

² SRMR was not reported because of missing value option.

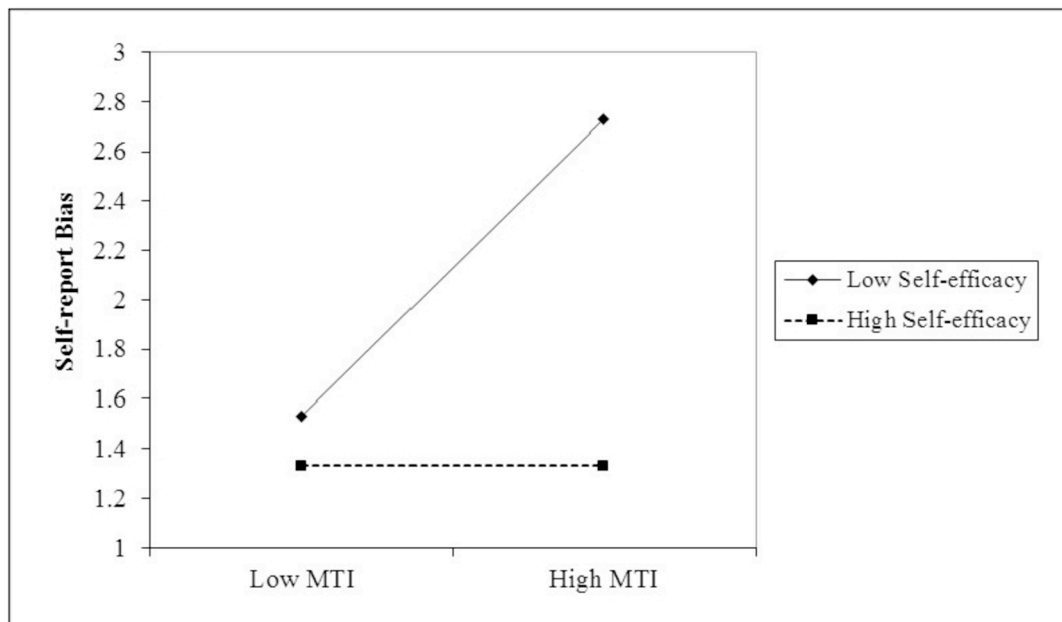


Fig. 3. Interaction effect.

identify themselves with mobile technology are more biased in their self-reports, thus H2 is rejected. Our search around the negative effects of technology identity showed that it could be due to reasons such as high dependency on technology. For example, [Shu, Tu, and Wang \(2011\)](#) showed that technology dependency is positively associated with techno-stress which has negative effects on people's life (i.e., anxiety, lack of focus, and so forth). Logically, these factors affect individual's self-reports. For example, a subject with high technology dependency and high techno-stress could experience anxiety during her data-entry and (s)he might misreport her physical wellness measures.

On the other hand, the moderation analysis shows that higher levels of perceived self-efficacy and higher levels of perceived MTI together negatively influence Self-report bias ($\beta = -0.41$ $p < 0.020$). Hence, H3 is supported. By extension, individuals with high self-efficacy who also happen to have high identity will measure and report their physical wellness factors more reliably. [Fig. 3](#) illustrates the interaction effect. As one could observe, when perceived Self-efficacy is high the Self-report bias score is at its minimum. However, for low perceived Self-efficacy, the Self-report bias score increases (from about 1.6 to 2.8). This will point at the fact that high perceived Self-efficacy is very important in self-report reliability context. Prior literature established that self-efficacy plays an important role in effective use of technology ([Compeau & Higgins, 1995](#); [Compeau, Higgins, & Huff, 1999](#)), and our results are consistent that in conjunction with identity self-efficacy reduces self-report biases on the m-Health app.

6. Discussion

Technology identity is viewed as a key factor in technology use ([Carter & Grover, 2015](#)). Given that smartphones are widely used by the public across the world they are becoming part of the individual's identity ([Carter & Grover, 2015](#)). Therefore, in this paper we utilized MTI theory and self-efficacy to study and address one of the contemporary issues identified in both literature and businesses ([Bardage et al., 2005](#); [Bowring et al., 2012](#); [Froom et al., 2004](#); [Gorber et al., 2007](#); [Kaplan & Baron-Epel, 2003](#); [Shmueli, 2003](#); [Shmueli et al., 2008](#); [Taylor et al., 2006](#)). By extension, utilizing smartphones to provide healthcare services would require patients to interact with technology with the absence of physicians and nurses, therefore the patient's tend to precisely measure and report their physical wellness status (such as

weight, height, blood pressure and so forth) becomes very crucial.

In short, our findings suggest that people holding an academic degree are more accurate in their weight and height reports (consistent with H1c). There is a well-established association between education and "health lifestyle" ([Ross & Wu, 1995](#)). Individuals who hold an academic degree are more prone to understand and be aware of health risks so they are more motivated to report their health status more accurately. Furthermore, the education they receive affects their knowledge of correctly measuring their health status. In addition, people with higher education are more exposed to technology and given that in this study individuals used apps to report academically educated individuals performed better.

We also found that elderly people show greater accuracy in their blood pressure report (consistent with H1a). Older adults may be familiar with self-monitoring and how to measure their health status because of their prior experience in visiting physicians. Besides, elders are more exposed to health risks such as high (or low) blood pressure which is a leading factor in causing death globally ([Stevens, Masearenhas, & Mathers, 2009](#)). Consequently, they are highly motivated to put efforts in accurately measuring and reporting their blood pressure.

The results of the theoretical model show a positive effect of perceived MTI on self-report bias. This implies a negative effect of MTI on self-report reliability, in contrast to the positive effect that we expected (H2). The results also show that self-efficacy is an important factor in predicting self-report reliability, consistent with earlier findings that self-efficacy improves performance ([Wu et al., 2007](#)). In addition, high levels of self-efficacy cause the MTI to positively affect self-report reliability (consistent with H3). Prior literature shows that self-efficacy plays an important role in the effective use of technology one of which could be improving self-report reliability ([Compeau & Higgins, 1995](#); [Compeau et al., 1999](#)).

7. Practical implications and future studies

This study makes several contributions to theory and practice. In regard to the theory, this study showed that self-efficacy is an important factor for self-report reliability, to the extent that it moderates the effect of MTI on self-report reliability. Also, the approach that we used in the estimation of self-report bias could be benchmarked by future

researchers in healthcare to estimate self-report bias. For the most part, the literature focused on demographical effects, but we extend the literature on self-report reliability in the context of m-Health apps by demonstrating self-efficacy and MTI are playing an important role. Furthermore, the results shed light on the difference that education could bring to self-report bias estimates. By extension, academically educated individuals showed a more reliable report of their height and weight.

Practitioners should direct their focus on making m-Health apps available and accessible to elderly people because they are the most reliable target population who can report themselves with less bias compared to others. Furthermore, m-Health app developers should invest their efforts in finding ways to elevate self-efficacy and perceived MTI among users of m-Health apps. The engagement and motivation aspect is captured through emotional energy dimension of MTI, so we recommend adding gamification elements given that recent works established it as an effective mean for engaging users (Seaborn & Fels, 2015).

In addition, we recommend that future researchers investigate the direct effect of MTI on self-report reliability. Per analyses, MTI increases the bias in self-report which is counterintuitive. Hence, there is a need for more research on the direct effect of MTI on self-report reliability. The alternative explanation could be that due to omission of Relatedness dimension (as discussed it could not pass the reliability and validity tests) of MTI, this construct is not as representative as it should be, even though it is a reflective construct by definition, still omitting a variable from it could slightly affect the direction and magnitude of the predictions (Diamantopoulos & Siguaw, 2006; Petter, Straub, & Rai, 2007). Moreover, there is a need for further longitudinal studies on both self-reliability reports as well as MTI. Individuals could have been misreporting themselves because of being new to the app or not knowing how to precisely measure their physical wellness status. If so,

the bias should diminish over the course of time. Similarly, longitudinal effects could affect MTI intensity in people.

Like all studies, this study has limitations. First, our data comes from a survey questionnaire. Survey data has potential issues such as high measurement errors (Podsakoff et al., 2003). We advise that future researchers try to identify and show how identity behaviors affect self-reliability report through archival data or log data of actual use pattern and interactions with m-Health apps. Second, given that this survey was not collected by enforcing participants to answer all questions, we have some missing values that we tried to address using ‘missing value’ estimation option in STATA SEM. Lastly, we relied on a single source for data collection that is we have one sample for this study. For the sake of generalizability and triangulations (Orlikowski & Baroudi, 1991), it is recommended that more samples and different methods can help to understand and predict a phenomenon better.

8. Conclusion

In conclusion, this study tried to address three research questions. The first question was concerned about the effect of demographic characteristics on the individual's tendency to accurately report their height, weight, and blood pressure on the m-Health app. The analyses illustrated that how education and age affect self-reports. The second question was with respect to the effect of perceived MTI on self-report reliability. Surprisingly, we found no such effect and called for further research on this topic. One possible explanation was that high levels of technology dependency create negative effects like anxiety that causes bias in self-reports (Shu et al., 2011). The last question addressed whether self-efficacy moderates the effect of MTI on self-report reliability. Per Fig. 2, the moderation effect exists and for high levels of self-efficacy, MTI is negatively associated with self-report bias.

Appendix

Measurement items				
Items	λ	Mean	St.d.	Cronbach's alpha
Mobile Technology Identity^a:	–	3.14	0.95	0.72
Dependence	0.87	3.56	1.16	0.79
Thinking about myself in relation to a mobile device, I feel dependent on mobile device.	0.82	3.42	1.50	
Thinking about myself in relation to a mobile device, I feel needing the device.	0.70	4.00	1.23	
Thinking about myself in relation to a mobile device, I feel reliant on the device.	0.73	3.26	1.39	
Emotional Energy	0.82	2.72	0.97	0.74
Thinking about myself in relation to a mobile device, I feel energized.	0.63	3.14	1.12	
Thinking about myself in relation to a mobile device, I feel enthusiastic about the device.	0.84	2.88	1.28	
Thinking about myself in relation to a mobile device, I feel pumped up.	0.64	2.13	1.18	
Self-efficacy^b:	–	3.84	1.07	0.83
I believe I can complete this medical report using mobile technology if there was no one around to tell me what to do.	0.83	3.92	1.20	
I believe I can complete this medical report using mobile technology even if I have never used a similar technology before.	0.71	3.68	1.28	
I am confident that I can effectively report medical information using mobile technology.	0.83	3.91	1.24	

^a Adopted from: Carter (2012); Carter and Grover (2015); Carter et al. (2013, pp. 150–164).

^b Adopted from: Davis (1985); Liao et al. (2009).

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