Consumer Adoption of Digital Technologies for Lifestyle Monitoring

Luca Gastaldi

Department of Management, Economics and Industrial Engineering
Politecnico di Milano
Via Lambruschini 4b, Building 26b, 20156 Milan (Italy)
E-mail: luca.gastaldi@polimi.it

Debora Bettiga *

Department of Management, Economics and Industrial Engineering
Politecnico di Milano
Via Lambruschini 4b, Building 26b, 20156 Milan (Italy)
E-mail: debora.bettiga@polimi.it

Emanuele Lettieri

Department of Management, Economics and Industrial Engineering
Politecnico di Milano
Via Lambruschini 4b, Building 26b, 20156 Milan (Italy)
E-mail: emanuele.lettieri@polimi.it

Lucio Lamberti

Department of Management, Economics and Industrial Engineering
Politecnico di Milano
Via Lambruschini 4b, Building 26b, 20156 Milan (Italy)
E-mail: lucio.lamberti@polimi.it

* *Corresponding author*

Keywords: Wearable devices; technologies for lifestyle monitoring; theory of planned behavior; online literacy; perceived doctor opinion.

Abstract

Despite their potential, the adoption of wearable devices has been relatively slow when compared to other digital technologies. This paper investigates, grounding on the Theory of Planned Behaviour, the adoption by end users of digital technologies for lifestyle monitoring. Data on consumers' perception and usage of wearable devices have been collected through a survey administered to 1,000 Italian citizens and further analysed through a Structural Equation Model approach. Results show that, above the functional value of the device, external influence, particularly doctor opinion, exerts an essential role in adoption. Online health literacy proves to be a relevant factor as well, showing the importance of cultural patterns in wearables diffusion. Implications for academicians, practitioners and policymakers are provided.

1 Introduction

Wearables devices have emerged as rapidly developing technologies with the potential to change people's lifestyles and improve their wellbeing, decisions, and behaviours [1]. However, the adoption of these devices has been relatively slow when compared to mainstream technologies such as smartphones [2]. Hence, both practitioners and academics show a growing interest in understanding the influential factors that explain a continued adoption of these technologies for lifestyle monitoring [3]. Technology adoption processes, indeed, represent a fundamental piece of knowledge to favour the diffusion of innovation [4] especially where such a diffusion may support the adoption of virtuous practices by users [5], as in the case of wearables. In contexts in which public healthcare systems are exposed to budgetary constraints, disease prevention, also through the support to functional, healthy conducts and lifestyles becomes of the essence to ensure welfare sustainability [6]. In this study, following a rich stream of literature on technology adoption (e.g. [7–9]), we analyse the adoption by end users of digital technologies for lifestyle monitoring, in order to understand possible drivers of their adoption and to draw implications for academicians, practitioners and policy makers.

2 Theory and Hypotheses

Studies that have investigated the influential factors in adopting wearable technologies have applied different approaches, and most of them have based their study designs on the well-known technology acceptance model and related consumer psychology theories [10–12]. Grounding on such studies, we advance that the Theory of Planned Behavior (TPB) [13] may be used to model the adoption of digital technologies in lifestyle monitoring. TPB was firstly proposed as an extension of the Theory of Reasoned Action, which was developed to predict voluntary behaviours and to understand their determinants [14]. The TPB postulates that behavioural Intention is the first predictor of behaviour since it captures people's motivations to perform it, showing how hard they are willing to try to perform it and how much effort they are planning to exercise. Intention is determined by three conceptually independents constructs: Attitude toward the behaviour (A), Subjective Norms (SN) and Perceived Behavioural Control (PBC). Attitude refers to the overall evaluation of the behaviour (positive or negative), and the more positive is the Attitude toward a behaviour, the higher will be the intention to perform it. Subjective Norms reflect the perceived social pressure by important others to perform the behaviour and they positively affect behavioural intention. Perceived Behavioural Control refers to the perceived ease or difficulty of engaging in the behaviour: the more people feel to have control over the behaviour, the more likely they will try to engage in it [13]. TPB is a widely applied theory to understand and predict human behaviours [15–17] and has been proved particularly effective in predicting health behaviours [18–20], thus representing a valid conceptual and theoretical background for this study. In particular, given the specificities of the behavior investigated, related to healthcare, we propose to focus our attention on a specific subjective norm, i.e. the doctor opinion. Adoption of technology for preventive healthcare, indeed, is not only pushed by individual beliefs, but is motivated by social pressure as well [5, 21]. This focus could also improve our understanding of the healthcare systems in the adoption processes of these technologies. For this reason, in this study we will test the following hypotheses:

H1a. The perceived utility of using digital technologies to monitor lifestyle has a positive influence on the development of a positive attitude toward this behaviour.

H1b. The attitude of using digital technologies to monitor lifestyle has a positive influence over the intention to do it.

H1c. The perceived control over the use of digital technologies to monitor lifestyle has a positive influence over the intention of doing it.

H1d. The perceived control over the use of digital technologies to monitor lifestyle has a positive influence over the implementation of this behaviour.

H1e. The intention to use digital technologies to monitor lifestyle has a positive influence over the implementation of this behaviour.

H2. The perceived doctor opinion on the monitoring of daily activities with a digital device has a positive influence on the intention to do it.

In order to understand to which extent the external, health-related lever of adoption (i.e., the doctor) is able to motivate users to adopt the technologies, we further investigated the role of individuals' health literacy in adopting the technologies [22]. Despite consumers are more and more inclined to look for information in different media and channels [23, 24], health literacy could be still improved [25]. Patients with low literacy experience poorer general health status and use of health resources [26, 27]. Grounding on that, we hypothesize that users more aware about healthcare and more prone to autonomously look for health-related information through digital channels, should modify their model of behavior with respect to the users that are less literate in this regard. More formally:

H3. The confidence an individual has on searching for health information on internet has an influence on the adoption of digital technologies to monitor lifestyle.

The conceptual model on which this study is base is depicted in Figure1. The model includes also four control variables that are consistent with past research on user acceptance models in wearable settings [2]: age, level of education, frequency of sport activities and the presence of a chronic disease.

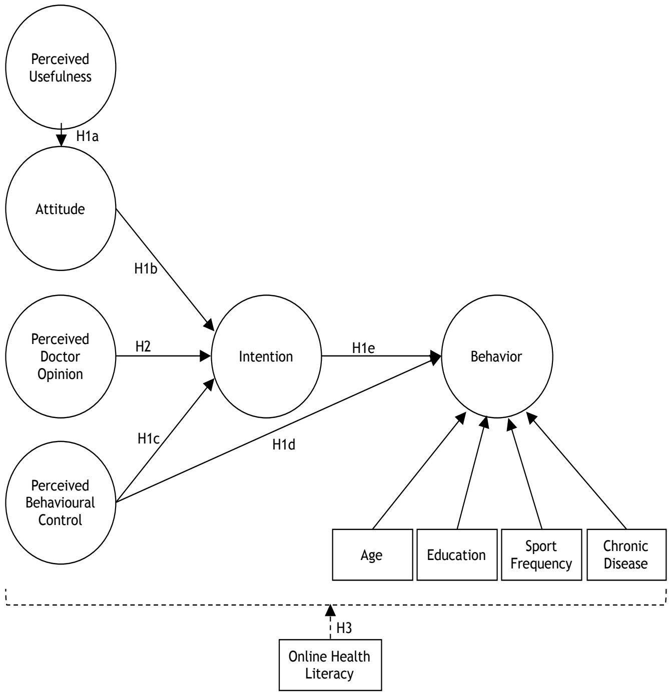


Figure 1 – Conceptual model and related hypotheses

3 Methods

To ensure content validity we developed our questionnaire by building on previous theoretical basis. To assure face validity, pre-testing was conducted using a focus group involving academics from the field and semi-structured interviews with selected participants who were not included in the subsequent research. We used a structured questionnaire mostly based on a ten-point Likert scale (for further details, see Table 1 in the Appendix). Measurement items were developed based on the literature review and supported by expert opinions.

The data were collected through a survey administered to 1,000 citizens who are statistically representative of the Italian population. The participants were given introduction letters that explained the aims and the procedures of the study.

Data analysis was carried out using Partial Least Square – Structural Equation Modeling (PLS–SEM). The estimation and data manipulation were performed using SmartPLS3. We opted for PLS-SEM due to the explorative type of research [28]. We performed a path analysis on the full model and further conducted a multi-group comparison between subjects with a low Online Health Literacy (below sample average) against subjects with a high Online Health Literacy (above sample average). Our sample size was satisfactory, being more than 10-times the largest number of structural paths directed to a particular latent construct in the structural model [29]. Our model was balanced in the weight of endogenous and exogenous constructs, meeting PLS-SEM's prediction goal [30].

4 Results

4.1 Measurement of Reliability and Validity

We firstly examined the reliability and validity measures for the model constructs (see Table 2 and Table 3 in Appendix). The number of iterations to find convergence was 5, suggesting the goodness of the model [31].

We measured composite reliability and Cronbach's alpha, as tests of convergent validity in reflective models (for a discussion see [32]). All our values exceed the suggested threshold of 0.7 for both composite reliability and Chronbach's alpha, thus confirming the validity of our model.

We used AVE, reflecting the average communality for each latent factor in a reflective model, as a test of both convergent and divergent validity. AVE values were above the threshold of 0.5 [33, 34] indicating convergent validity, thus the latent construct ability to explain a great share of the variance of its indicators. Further, we establish discriminant validity by the Fornell–Larcker criterion [35], which assesses discriminant validity on the construct level, by assessing that the square root of AVE is higher than its correlation with any other latent variable. All our AVE square roots were satisfying this condition. At the indicator level, we evaluated discriminant validity by assessing that the loading of each indicator is greater than all of its cross-loadings [33]. We satisfied this criterion as well.

As a measure of fit of the model, we evaluated the standardized root mean square residual (SRMR). Our model has a SRMR below the suggested maximum value of 0.08 [36] thus confirming the good fit.

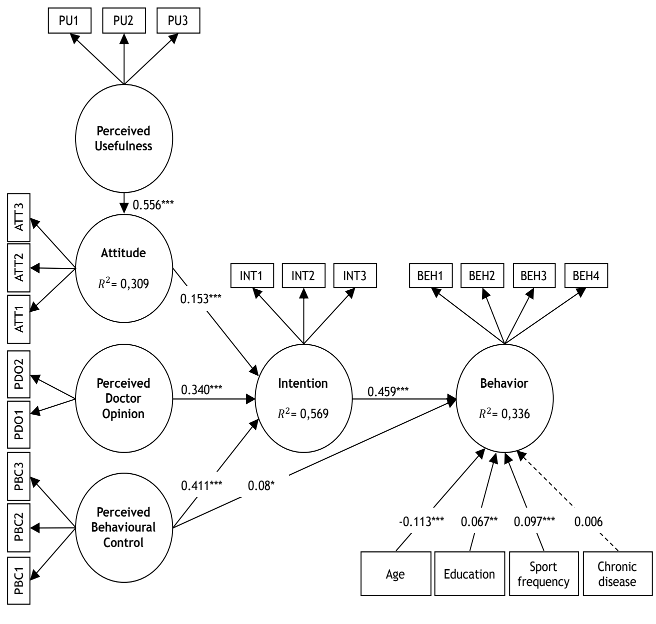
Finally, we checked our model for structural multi-collinearity. Our structural Variance Inflation Factor (VIF) coefficients are lower than 4 [37], suggesting that multicollinearity is not an issue in our model.

4.2 Results of Model Estimations

After validating the measurement model, the hypothesized relationships among the constructs were tested. A bootstrapping with 5,000 samples was conducted [37]. The structural model was then assessed by examining the determination coefficients, the path coefficients and their significance levels.

As shown in Figure 2, all hypotheses are fully supported, with path coefficients significant at the 0.05 significance level and below. Individual-specific variables of age, education and sport frequency shown a significant, even if small, influence. The presence of a chronic disease instead does not have influence on the adoption of digital technologies to monitor lifestyle. The coefficient of determination R^2 is of 0.309 for attitude, 0.569 for intention and 0.336 for behavior, representing adequate effects for our model.

Blindfolding technique [38] was used as a measure of predictive relevance of the model, by calculating the Q^2 value [39, 40]. Q^2 values above zero indicate that the observed values are adequate reconstructed and that the model has predictive relevance [41]. The Q^2 value of cross-validated redundancy is 0.204 for attitude, 0.476 for intention and 0.202 for behavior, showing respectively medium to large effect size according to [42].



Note: *p-value <0,05; **p-value < 0,01; ***p-value < 0,001

Note: significant paths are represented by full arrows, non-significant ones by dotted arrows

Figure 2 – Structural model results

4.3 Multi-Group Analysis (MGA)

PLS multigroup analysis has been used to assess if the proposed model differs between individuals with high and with low online health literacy. Two groups were defined discriminating on the OHL mean (5.09) resulting in 490 subjects with high OHL and 414 subjects with low OHL. A bootstrapping with 5,000 samples has been conducted [37].

Path coefficients, standard deviations and coefficient of determination R^2 for the two groups are reported in Table 4 in Appendix. The results of the non-parametric significance test for the difference between group-specific path coefficients are reported as well (see [41, 43]). As noted, a significant difference (p-value <0.05) between the two groups is found for the following relationships: attitude on intention, intention on behaviors and perceived behavioral control on behavior. The other paths do not show differences between the groups.

Given the results of the empirical study, table IV summarizes the outcomes of the hypothesis testing advanced in this empirical exercise.

5 Discussion, Implications and Conclusions

The results of the study raise a number of relevant implications for academicians, practitioners and policy makers. First and foremost, the study demonstrates how the Theory of Planned Behavior [13] may describe and explain the adoption of digital technologies for lifestyle monitoring, showing in particular that the process is significantly cognitive in nature, given the strong relationship between intention and behavior. As emerged in other studies [44, 45], a direct – though not particularly strong - relationship between Perceived Behavioral Controls and Behavior emerges, raising the idea that habits and confidence in the instruments may be a good driver of adoption, even beyond the intrinsic intention to adopt. Remarkably, Attitude results strongly determined by the construct of Perceived Usefulness, testifying that the opinion on these devices is still strongly tied to the perception of their functional value [46]. What characterizes our results, yet, is the fact that, compared to traditional TPB-based studies, our work shows that Perceived Doctor Opinion (the stronger Subjective Norm we may imagine in this adoption process) and Perceived Behavioral Control play a stronger role in the development of an Intention than Attitude. This is a remarkable result, in that it shows that the adoption of digital technologies for lifestyle monitoring depends not only on personal beliefs, but also, and probably foremost, on the perception of appreciation by the doctors and by the perception of ability to buy and use the technology. This outcome lets hypothesize that the main driver of adoption is external in nature, and highlights the weight and importance of third parties', authoritative influencers in increasing the intention to adopt and, in turn, the actual adoption of lifestyle monitoring technologies. This is strongly supported by the outcomes of H3 testing, showing that Online Health Literacy boosts the internal motivations to adopt, i.e., the role of attitude in TPB. The analysis of the covariates further shows that in our sample, which is a reliable (both in terms of size and composition) representation of the Italian population, the digital technologies for Lifestyle monitoring are particularly adopted by younger, more educated and sporty users, while there is not an apparent influence of the presence of chronic diseases in the adoption process. This outcome shows how, besides the external nature of the adoption process, cultural patterns are of the essence in this kind of innovation diffusion. This suggests practitioner and policy makers alike to advance proper communication and promotion campaigns towards elder and less educated layers of the population to increase their actual adoption. The results of our study show that the potentially most effective levers of communication refer to an increase of doctors' awareness on the usefulness of these solutions (of course, if existing), but also on their ease of use by the users.

References

1. Wright R, Keith L (2014) Wearable technology: If the Tech Fits, Wear It. J Electron Resour Med Libr 11:204–216.
2. Kalantari M (2017) Consumers adoption of wearable technologies: literature review, synthesis, and future research agenda. Int J Technol Mark 12:1
3. Wang YH, Hsieh CC (2018) Explore technology innovation and intelligence for IoT (Internet of Things) based eyewear technology. Technol Forecast Soc Change 127:281–290.
4. Bettiga D, Lamberti L (2017) Exploring the adoption process of personal technologies: A cognitive-affective approach. J High Technol Manag Res 28.
5. Bettiga D, Lamberti L, Lettieri E (2019) Individuals' adoption of smart technologies for preventive health care: a structural equation modeling approach. Health Care Manag Sci.
6. Cohen JT, Neumann PJ, Weinstein MC (2008) Does Preventive Care Save Money? Health Economics and the Presidential Candidates. N Engl J Med 358:661–663.
7. Tanawat H, Audhesh KP (2006) Consumer innovativeness and perceived risk: implications for high technology product adoption. J Consum Mark 23:182–198
8. Bettiga D, Lamberti L, Noci G (2017) Do mind and body agree? Unconscious versus conscious arousal in product attitude formation. J Bus Res 75:108–117.
9. Bettiga D, Lamberti L (2018) Exploring the role of anticipated emotions in product adoption and usage. J Consum Mark 35:300–316.
10. Davis FD (1993) User acceptance of information technology: system characteristics, user perceptions and behavioral impacts. Int J Man Mach Stud 38:475–487.
11. Venkatesh V, Davis FD (2000) A Theoretical Extension of the Technology Acceptance Model: Four Longitudinal Field Studies. Manage Sci 46:186–204.
12. Holden R, Karsh B (2010) The Technology Acceptance Model: Its past and its future in health care. J Biomed Inform 43:159–172.
13. Ajzen I (1991) The theory of planned behavior. Organ Behav Hum Decis Process 50:179–211.
14. Madden TJ, Ellen PS, Ajzen I (1992) A Comparison of the Theory of Planned Behavior and the Theory of Reasoned Action. Personal Soc Psychol Bull 18:3–9.

15. Steinmetz H, Knappstein M, Ajzen I, et al (2016) How effective are behavior change interventions based on the theory of planned behavior?: A three-level meta analysis. Zeitschrift fur Psychol. / J. Psychol. 224:216–233

16. Ajzen I (2015) Consumer Attitudes and Behavior: the Theory of Planned Behavior Applied to Food Consumption Decisions. Riv di Econ Agrar 2:121–138

17. Riebl, S. K., Estabrooks, P. A., Dunsmore, J. C., Savla, J., Frisard, M. I., Dietrich, A. M, Y., Peng, X., Zhang, B.M. D (2015) A systematic literature review and meta-analysis: The Theory of Planned Behavior's application to understand and predict nutrition-related behaviors in youth. Eat. Behav. 18:160–178

18. Bohon LM, Cotter KA, Kravitz RL, et al (2016) The Theory of Planned Behavior as it predicts potential intention to seek mental health services for depression among college students. J Am Coll Heal 64:593–603.

19. Hagger MS, Chan DKC, Protogerou C, Chatzisarantis NLD (2016) Using meta-analytic path analysis to test theoretical predictions in health behavior: An illustration based on meta-analyses of the theory of planned behavior. Prev Med (Baltim) 89:154–161.

20. Cooke, R., Dahdah, M., Norman, P., & French DP (2013) How well does the theory of planned behaviour predict alcohol consumption ? A systematic review and meta-analysis. Health Psychol Rev 102:148–167

21. Ong L, de Haes JCJM, Hoos AM, Lammes FB (2003) Doctor-patient communication: A review of the literature. Soc Sci Med 40:903–918.

22. Rudd RE (2015) The evolving concept of Health literacy : New directions for health literacy studies. J Commun Healthc 8:7–9.

23. Bettiga D, Boaretto A, Chen S (2013) Exploring media convergence: Evidence from Italy. Int J Eng Bus Manag 5:1–9.

24. Fernández-Luque L, Bau T (2015) Health and social media: Perfect storm of information. Healthc. Inform. Res. 21:67–73.

25. Sørensen K, Van Den Broucke S, Fullam J, et al (2012) Health literacy and public health: A systematic review and integration of definitions and models. BMC Public Health 12:80.

26. DeWalt DA, Berkman ND, Sheridan S, et al (2004) Literacy and health outcomes. J Gen Intern Med 19:1228–1239.

27. Berkman ND, Sheridan SL, Donahue KE, et al (2011) Low health literacy and health outcomes: An updated systematic review. Ann. Intern. Med. 155:97–107.

28. Hwang H, Malhotra N, Kim Y, et al (2010) A comparative study on parameter recovery of three approaches to structural equation modeling. J Mark Res 47:699–712.

29. Barclay D, Higgins C, Thompson R (1995) The Partial Least Squares (PLS) Approach to Causal Modelling: Personal Computer Adoption and Use as an Illustration. Technol Stud 2:285–309.

30. Hair J, Sarstedt M, Ringle C, Mena J (2012) An assessment of the use of partial least squares structural equation modeling in marketing research. J Acad Mark Sci 40:413–433.

31. Wong K (2013) Partial least squares structural equation modeling (PLS-SEM) techniques using SmartPLS. Mark Bull 24:1–32.

32. Werts C, Linn R, Jöreskog K (1974) Intraclass reliability estimates: Testing structural assumptions. Educ Psychol Meas 34:25–33.
33. Chin W (1998) The partial least squares approach to structural equation modeling. Mod methods Bus Res 295:295–336.
34. Bagozzi RP, Yi Y (1988) On the evaluation of structural equation models. J Acad Mark Sci 16:74–94.
35. Fornell C, Larcker D (1981) Evaluating structural equation models with unobservable variables and measurement error. J Mark Res 18:39–50.
36. Hu LT, Bentler PM (1999) Cutoff criteria for fit indexes in covariance structure analysis: Conventional criteria versus new alternatives. Struct Equ Model 6:1–55.
37. Hair J, Ringle C, Sarstedt M (2011) PLS-SEM: Indeed a silver bullet. J Mark Theory Pract 19:139–152
38. Tenenhaus M, Vinzi V (2005) PLS path modeling. Comput Stat Anal 48:159–205
39. Stone M (1974) Cross-validatory choice and assessment of statistical predictions. J R Stat Soc Ser B 36:111–147.
40. Geisser S (1974) A predictive approach to the random effect model. Biometrika 61:101–107.
41. Henseler J, Fassott G (2010) Testing moderating effects in PLS path models: An illustration of available procedure. In: Handbook of Partial Least Squares. Springer Berlin Heidelberg, pp 171–193.
42. Cohen J (1988) Statistical power analysis for the behavioral sciences. Lawrence Erlbaum Associates, Hillsdale, New Jersey.
43. Sarstedt M, Henseler J, Ringle C (2011) Multigroup analysis in partial least squares (PLS) path modeling: Alternative methods and empirical results. Adv Int Mark 22:195–218.
44. Ajzen I, Madden TJ (1986) Prediction of goal-directed behavior: Attitudes, intentions, and perceived behavioral control. J Exp Soc Psychol 22:453–474.
45. Godin G, Kok G (1996) The Theory of Planned Behavior: A Review of its Applications to Health-Related Behaviors. Am J Heal Promot 11:87–98.
46. Sheth JN, Newman BI, Gross BL (1991) Why we buy what we buy: A theory of consumption values. J Bus Res 22:159–170.

Appendix

Table I. Indicator of the measurement model

Construct	Label	Indicator
Attitude	ATT1	Heath rate monitoring is important for staying well
	ATT2	Steps monitoring is important for staying well
	ATT3	Training monitoring is important for staying well
Behavior	BEH1	Usage of apps to monitor hearth rate
	BEH2	Usage of apps to monitor steps
	BEH3	Usage of apps to monitor training through the wearable device
	BEH4	Usage of apps to monitor calories through the wearable device
Intention	INT1	I planned to monitor my lifestyle with digital devices in the upcoming months
	INT2	It is probable that I'll monito my lifestyle with digital devices in the upcoming months
	INT3	I intent monitoring my lifestyle with digital devices in the upcoming months
Perceived Behavioral Control	PBC1	I have enough time to monitor my lifestyle with digital devices
	PBC2	I have enough economic resources to monitor my lifestyle with digital devices
	PBC3	Monitoring my lifestyle with digital devices is easy
Perceived Doctor Opinion	PDO1	My doctor thinks that I should monitor my lifestyle with digital devices
	PDO2	My doctor expects me to monitor my lifestyle with digital devices
Perceived usefulness	PU1	Monitoring my lifestyle with digital devices would improve my health conditions
	PU2	Monitoring my lifestyle with digital devices would enable me to maintain healthy
	PU3	Monitoring my lifestyle with digital devices is useful
Online Health Literacy	OHL1	I know how to use internet for answering to questions about my health condition
	OHL2	I am able distinguishing valuable resources from unevaluable one while searching online for health information
Control variables	EDU	Education [9 = University degree; 8 = Univ. without diploma; 7 = College degree; 6 = College without diploma 5 = High school degree; 4 = High School without diploma 3 = Elementary school degree; 2 = Elementary school without diploma; 1 = no education]
	SPORT	Frequency of sport activities [6 = three times per week; 5 = once a week; 4 = once a month; 3 = once a year; 2 = less than once a year; 1 = never]
	CHR	Presence of a chronic diseases [1 = Yes; 0 = No]
	AGE	Age of the respondent in years

Note: all indicators except those related to the Behavior construct are measured on a Likert scale from 1 to 10 (1 = complete disagreement with the statement; 10 = complete agreement with the statement in the). The indicators related to Behavior have values from 1 to 3 (1 = Not using and not interested; 2 = Not using but interested; 3 = Using).

Table II. Descriptive statistics, reliability and validity measures

Constructs	Estimates				Indicators	Final model			
	Cronbach α	*Rho_A*	*Reliability*	*AVE*		*Valuable obs.*	*Mean*	*Std. Dev*	*Loadings*
Attitude	0.785	0.788	0.874	0.699	ATT1	953	7.406	2.607	0.821
					ATT2	943	6.017	2.967	0.838
					ATT3	934	6.278	2.920	0.849
Behavior	0.814	0.815	0.877	0.641	BEH1	1000	1.421	0.685	0.774
					BEH2	1000	1.327	0.639	0.815
					BEH3	1000	1.322	0.622	0.813
					BEH4	1000	1.304	0.581	0.800
Intention	0.937	0.937	0.960	0.888	INT1	949	3.906	2.988	0.942
					INT2	945	4.013	2.992	0.943
					INT3	950	4.031	3.067	0.942
Perceived Behavioral Control	0.762	0.772	0.863	0.677	PBC1	949	4.897	2.969	0.847
					PBC2	927	4.790	2.936	0.768
					PBC3	907	5.490	2.864	0.851
Perceived Doctor Opinion	0.764	0.766	0.894	0.809	PDO1	860	5.098	2.929	0.893
					PDO2	910	3.754	2.779	0.906
Perceived Usefulness	0.899	0.899	0.937	0.831	PU1	935	5.084	2.993	0.913
					PU2	942	5.134	2.979	0.915
					PU3	951	5.472	2.998	0.907
Online Health Literacy	-	-	-	-	OHL1	928	5.109	3.052	-
					OHL2	921	4.988	2.866	-
Education	-	-	-	-	EDU	1000	6.491	1.570	-
Sport Frequency	-	-	-	-	SPORT	1000	3.612	2.104	-
Chronic Diseases	-	-	-	-	CHR	1000	0.286	0.452	-
Age	-	-	-	-	AGE	1000	52.51	16.60	-

Table III. Multi-Group Analysis Results

	OHL_HIGH (N = 490)		OHL_LOW (N = 414)		GROUP DIFFERENCES (| OHL.HIGH – OHL.LOW |)
	Path coefficients	*St dev*	*Path coefficients*	*St dev*	*Path coefficients*
Attitude → Intention	0.224***	0.038	0.110**	0.038	0.114*
Intention → Behavior	0.516***	0.048	0.316***	0.072	0.199**
Perceived Behavioral Control → Behavior	0.026	0.047	0.190**	0.062	0.164*
Perceived Behavioral Control → Intention	0.407***	0.043	0.360***	0.054	0.047
Perceived Doctor Opinion → Intention	0.303***	0.048	0.396***	0.059	0.094
Perceived Usefulness → Attitude	0.499***	0.040	0.560***	0.034	0.062
Age → Behavior	-0.100*	0.044	-0.132**	0.045	0.032
Chronic disease → Behavior	-0.037	0.039	0.055	0.045	0.092
Education → Behavior	0.053	0.039	0.073	0.042	0.020
Sport frequency→ Behavior	0.129***	0.035	0.054	0.042	0.075
Attitude	***R^2***		***R^2***		
Behavior	0.249		0.314		
Intention	0.339		0.267		
	0.539		0.529		

Note: * p-value <0.05; ** p-value < 0.01; *** p-value < 0.001

Table IV. Results of Hypothesis Testing

Hypothesis	Formulation	Result
H1a	The perceived utility of using digital technologies to monitor lifestyle has a positive influence on the development of a positive attitude toward this behavior.	Supported
H1b	The attitude of using digital technologies to monitor lifestyle has a positive influence over the intention to do it.	Supported
H1c	The perceived control over the use of digital technologies to monitor lifestyle has a positive influence over the intention of doing it.	Supported
H1d	The perceived control over the use of digital technologies to monitor lifestyle has a positive influence over the implementation of this behavior.	Supported
H1e	The intention to use digital technologies to monitor lifestyle has a positive influence over the implementation of this behavior.	Supported
H2	The perceived doctor opinion on the monitoring of daily activities with a digital device has a positive influence on the intention to do it.	Supported
H3	The confidence an individual has on searching for health information on internet has an influence on the adoption of digital technologies to monitor lifestyle.	Partially supported