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A mixed methods UTAUT2-based approach to assess mobile health adoption

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ABSTRACT

Drawing on UTAUT2, this study examines the number of causal recipes that foster mHealth adoption, using a mixed approach combining Partial Least Squares (PLS-SEM) and fuzzy-set qualitative comparative analysis. Two general research propositions are assessed using data collected through a survey administered to 120 mHealth users. The findings point that PLS-SEM and fsQCA are complementary analytical approaches providing comparable results. PLS-SEM indicates that performance expectancy, hedonic motivation, and habit have the ability to predict mHealth adoption, while fsQCA reveals six configurations including the factors identified by PLS-SEM. The findings suggest that several conditions that were not significant in PLS-SEM are in fact sufficient conditions when combined with other conditions. For practitioners concerned with fostering mHealth adoption, the findings stress the importance of adopting an integrated approach centered on performance expectancy, facilitating conditions, and habit, targeting well-educated young women. The existence of multiple solutions also points to the presence of equifinality.

1. Introduction

The extensive adoption of mobile technology in healthcare (mHealth) in developed countries is currently regarded as unavoidable due to increased costs associated with health monitoring. According to Statista (2019), the mHealth market size is growing steadily and it is expected to reach 58.8 billion U.S. dollars in 2020. The pace of adoption varies from country to country but is likely to be led by emerging markets that rank highest on the score of mHealth maturity and readiness where Portugal holds the 10th position among European countries (Statista, 2016).

According to a study by PriceWaterhouseCoopers (2014), consumers have high expectations for mHealth as they perceive it as a way to increase access to healthcare and to improve the convenience, cost, and quality of healthcare. If mHealth promises are able to fulfill consumers' expectations the impact on healthcare delivery could be substantial and may change the relationships within the healthcare business. Evidence of mHealth market vitality is the number of apps available in online stores. According to a study by Accenture (2018) on digital health, 48% of healthcare consumers are using mHealth apps, compared to just 16% in 2014. There are now over 318,000 health apps available on the top app stores worldwide, nearly double the number of apps available in 2015 and > 200 apps being added each day (IQVIA Institute, 2017). The global mHealth app market is projected to be valued at US$28.32 billion in 2018 and is expected to reach up to US $102.35 billion by 2023 (Knowledge Sourcing Intelligence, 2017). It is also expected that the increased adoption of smartphones, as well as the continuous investment into the digital health market, would be the main factors driving the growth of the mHealth market.

Healthcare companies are exploring strategies to adapt to this emerging and vibrant digital marketplace through the adoption of mHealth digital technologies (Hird, Ghosh, & Kitano, 2016). For healthcare companies, there has been a growing recognition that digital technologies must be part of future consumer offerings to remain competitive within the healthcare industry. Despite the extensive offer and the obvious potential benefits of mHealth, massive adoption has still not occurred. The use of mHealth and speed of adoption will be determined by stakeholders' response to mHealth, the overcome of structural impediments and the capacity to align the benefits around patients' needs and expectations. A lack of clarity on how consumers engage with and persist in using digital products for health self-management remains a significant challenge for healthcare companies in developing effective digital strategies (Hird et al., 2016). The central barriers are not technology-related but systemic to the healthcare industry and the individual's natural resistance to change. Though many people regard mobile health as supplementary to the healthcare industry, mHealth should instead be regarded as the future of healthcare by making health services better, faster, less expensive, and more

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customer-focused.

Despite the exponential growth of mHealth, there are still challenges to overcome the massive adoption of mHealth technologies (devices and applications) (Gurupur & Wan, 2017). Grounded on the robust technology adoption framework UTAUT2 (Venkatesh, Thong, & Xu, 2012) the current article focuses the user perspective by investigating the UTAUT2 dimensions that are relevant to address the challenges imposed to the extensive adoption of mHealth. Consistently, the main research question of this study is: What configurations of UTAUT2 dimensions (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation, price value, and habit) predict the willingness for adopting mHealth?

The remainder of this paper is structured as follows. Firstly, we address key relevant literature on factors and models used for explaining mHealth adoption. After, the methodology is presented. Finally, the results, conclusions, limitations, and future research are addressed.

1. Research on mHealth adoption

Despite being a rather recent topic in the literature there is already a significant body of research on mHealth adoption. The scientific research on mobile health adoption can be divided into two major groups according to the target population studied: healthcare services and professionals, and individuals. Since the focus of this investigation is the individual adopter, only the studies aimed at this group were considered for review. For those interested in the healthcare professionals' perspective two systematic reviews are available, namely by Gagnon, Ngangue, Payne-Gagnon, and Desmartis (2016), and Li, Talaei-Khoei, Seale, Ray, and MacIntyre (2013).

The research around mHealth adoption has mainly been based on well-known and established theoretical frameworks, specifically the Technology Acceptance Model (TAM), the Diffusion of Innovations Theory, and the Unified Theory of Acceptance and Use of Technology (UTAUT) and its extension, the UTAUT2 (Gücin & Berk, 2015). The UTAUT proposed by Venkatesh, Davis, and Davis (2003) includes three variables (performance expectancy, effort expectancy, and social influence) that affect behavioral intention to use a technology, one variable (facilitating conditions) that affects actual usage, and four moderators (age, gender, experience, and voluntariness). More recently, Venkatesh et al. (2012) proposed an extension to the original UTAUT by incorporating three new constructs (i.e., hedonic motivation, price value, and habit) and named it UTAUT2. This new framework explained 74% of the variance in consumers' behavioral intention to use technology and 52% of the variance in consumers' technology usage (Venkatesh, Thong, & Xu, 2016). The UTAUT framework has some advantages over other theoretical frameworks, namely: (1) The UTAUT was developed by considering previously developed models (e.g. the theory of reasoned action (TRA), TAM, the motivational model, the theory of planned behavior (TPB), and the innovation diffusion theory); (2) the UTAUT model has a superior explanation power when compared to other models (Lee & Rho, 2013).

Both the UTAUT and UTAUT2 frameworks have been used to explain the adoption of mHealth by both targets. Table 1 presents a comparison of the studies that used the UTAUT theoretical frameworks to assess the adoption of mHealth by individuals.

2. Research model and propositions

Based on the results on the acceptance of health information technologies and of mobile Health by Garavand, Samadbeik, Kafashi, and Abhari (2017) among other studies (e.g. Nisha et al., 2019), facilitating conditions, which expresses the conditions that make the use of technology easier, was the most cited factor affecting the acceptance of mobile health technology. The current review confirmed previous evidence on the importance of facilitating conditions but points also performance expectancy and effort expectancy as key factors affecting mHealth adoption. Another review by Wildenbos, Peute, and Jaspers (2017) matched the facilitators and barriers on health record patient portal adoption by older adults with the UTAUT dimensions and end up by proposing one UTAUT sub-concept for performance expectancy (benefits patient/provider relationship), five sub-concepts for voluntariness of use (level of education, health interest & status, dissatisfied with current care communication, satisfied with current care communication, and cultural background), two UTAUT sub-concepts for facilitating conditions (implementation issues, and concerns), and three sub-concepts for voluntariness of use (Health literacy, satisfied with current care communication, and motivation).

As for the current analysis (Table 1), the ability of the UTAUT theoretical framework variables to explain the adoption of mHealth vary according to the specific characteristics of the study (e.g. the sample, and the variables involved). Regarding the methods used, the review revealed that almost all studies used a quantitative approach, with a strong emphasis on regression and structural equation modeling (SEM). Additionally, the mixed results on the significance of the UTAUT variables for explaining mHealth adoption synthesized in Table 1, suggest that no single variable is per se neither necessary nor sufficient to fully and constantly explain behavioral intention toward mHealth. Considering the above conditions, the approach selected for this study combines two methodologies: Partial Least Squares (PLS) and fuzzy set Qualitative Comparative Analysis (fsQCA). While PLS-SEM evaluates pre-determined relationships that are expected to explain the dependent variable of interest, the fuzzy set QCA methodology allows assessing several alternative causal recipes concurrently (Ragin, 2006; Woodside, 2013). Therefore, instead of considering the unique influence of each variable on the outcome, fsQCA examines how causal conditions (independent variables) combine into several configurations entailing equifinality, thus conducing to the same outcome (dependent variable) (Fiss, 2007; Pappas, Kourouthanassis, Giannakos, & Lekakos, 2017). To a certain extent, it complements PLS-SEM results (Gelhard, von Delft, & Gudergan, 2016; Tóth, Thiesbrummel, Henneberg, & Naudé, 2015; Woodside, 2013).

The proposed conceptual models (Fig. 1) use the variables from the UTAUT2 theoretical framework (Performance Expectancy, Effort Expectancy, Social Influence and facilitating conditions, hedonic motivation, price value, and habit) as causal conditions and examines its effects on the adoption of mHealth (outcome). Age, gender, and education as a proxy for experience were used as moderators to retain consistency with the UTAUT2 model formulation. Based on this research objective, two broad propositions are offered.

Proposition 1. The seven UTAUT2 dimensions are not, by themselves, necessary to influence mobile Health adoption.

Proposition 2. The seven UTAUT2 dimensions are not, by themselves, sufficient to influence mobile Health adoption.

The rationale behind the formulations of these propositions is based on a comparative analysis of the significant factors for the adoption of mHealth in the studies cited in Table 1. From Table 2 It is possible to conclude that none of the conditions present a consistent significant or non-significant effect on mHealth adoption. This fact provides support to the propositions stating that the seven UTAUT2 dimensions are not, by themselves, either necessary or sufficient to influence mobile health adoption.

2. Methodology

2.1. Measures and data collection procedures

In terms of measurement, the UTAUT2 dimensions were operationalized using prior validated multi-item scales from Venkatesh et al. (2012) slightly adapted to comply with the mobile health context. The

Table 1
UTAUT framework usage to explain consumers' mHealth adoption.

Source	Methodology	Sample	Framework/ variables	Key findings/Validated relationships
(Hwabamungu & Williams, 2010)	Qualitative	42 South African HIV/AIDS Patients	UTAUT	Adoption is mostly dependent on: (1) the caregivers and patients' willingness and capability to incur any technological adoption and continuous use costs and, (2) their pre-conceived notions of government or sponsor-supported service provision.
(Boontarig, Chutimaskul, Chongsuphajaisiddhi, & Papasratorn, 2012)	Quantitative (Pearson Correlation Analysis and Linear Regression)	31 Thai elderly people	Extended UTAUT model which includes perceived value	Perceived value has a strong effect on the intention to use a smartphone, followed by facilitating conditions, and effort expectancy. in contrast, performance expectancy, and social influence did not have a significant influence on intention.
(Hsu, Lee, & Su, 2013)	Structural Equation Modeling With LISREL	280 undergraduate students	UTAUT Model plus Perceived Security, and Information Security Literacy.	Effort Expectancy, Information Security and literacy show no significant direct effects on behavioral intention. Total effects were all significant.
(Lee & Rho, 2013)	Two- independent samples *t*-test and one-way ANOVA Analysis	106 users 113 non-users from South Korea	UTAUT Model plus communication, service risk accessibility, and intimacy.	Age and gender appear to be discriminate user and non-users Only accessibility had no significant differences between users and non-users
(Kiongo, 2014)	Regression Analysis	129 individuals from Kenya	UTAUT Model plus Perceived Usefulness, Perceived Ease of use, Reliability, Cost, Motivation, Effectiveness, Awareness/Peer Influence, User Satisfaction, Confidence, and Fear	All variables are significant for predicting the intention to use mHealth. The model R-square is 0.642.
(De Veer et al., 2015)	Nested Linear Regression Analysis	1014 Dutch individuals	UTAUT plus educational level	The intention to use e-Health applications was mainly explained by performance expectancy, effort expectancy, and self-efficacy. No effect for social influence was found.
(Shareef, Ahmed, Kumar, & Kumar, 2015)	Structural Equation Modeling (SEM)	127 diabetic patients in Bangladesh and 115 in Canada	UTAUT	Results indicate significant differences in consumer perceptions of M-health operated through mobile phone-based SMS between Canada and Bangladesh. All the independent variables are found significant. For Bangladeshi consumers, Facilitating Conditions is the most important attribute where for Canadians is performance expectancy.
(Gao, Li, & Luo, 2015)	Partial Least Squares (PLS) Path Analysis	462 users of wearable devices from social network groups	UTAUT2, PMT, and privacy calculus theory. UTAUT2 without facilitating Conditions, price value, and Habit; plus, Functional Congruence, Self-Efficacy, Perceived Vulnerability, Perceived Severity, Perceived Privacy Risk	Findings indicate that all constructs exert a significant influence on the adoption. Self-efficacy, perceived severity, and perceived privacy risk are particularly important for medical wearables. For fitness wearables, functional congruence, hedonic motivation, and perceived privacy risk are the more important factor influencing the adoption.
(Boontarig, 2016)	Linear Regression	212 voluntary respondents with online social network experience	UTAUT model and Big Five personality traits as moderators	Findings indicate that facilitating conditions and perceived value had a significant effect on behavioral intention to use m-Health information through social media. Conscientiousness acts as moderator for facilitating conditions and perceived value
(Moon & Hwang, 2016)	Multiple-Regression Analysis	126 Korean College Students	UTAUT plus personal innovativeness, and perceived enjoyment	Findings suggest that social influence positively affects user intention to use, and that performance expectancy is positively correlated with the intention to use. Perceived enjoyment positively affects the potential intention to use the services. Personal innovativeness, effort expectancy, and facilitating conditions did show a significant effect on intention to use.
(Dwivedi, Shareef, Simintiras, Lal, & Weerakkody, 2016)	Path Analysis with LISREL	387 diabetic patients from the US, 375 from Bangladesh, and 396 from Canada	UTAUT2 plus waiting time, and self-concept	Hedonic motivation was not significant for the US and Canadian users, self-concept for Bangladeshi users. Effort expectancy and facilitating conditions are the two major contributors regardless of the country.
(Cimperman, Makovec Brenčič, & Trkman, 2016)	Path Analysis with LISREL	400 Slovenians aged 50 years and above	UTAUT plus Doctor's Opinion, Computer Anxiety, and Perceived Security as contextual predictors	Performance expectancy, effort expectancy, facilitating conditions, and perceived security were confirmed having a direct impact on behavioral intention to use home telehealth services.

(*continued on next page*)

Table 1 (*continued*)

Source	Methodology	Sample	Framework/ variables	Key findings/Validated relationships
(Dzimiera, 2017)	Partial Least Squares (PLS) Path Analysis	295 German citizens	UTAUT plus self-efficacy, Privacy and Security Risk, Surveillance Anxiety, and Physical Risk.	The research model has an R^2 value of 0.532. Effort expectancy, privacy and security risk, and physical risk have no significant effect on the behavioral intention to use mHealth. Performance expectancy is the major predictor. Self-efficacy was found to be a good predictor of effort expectancy ($R^2 = 0.639$).
(Idrish, Rifat, Iqbal, & Nisha, 2017)	Partial Least Squares (PLS) Path Analysis	908 Bangladeshi	UTAUT plus personal innovativeness, perceived self-efficacy, and perceived financial cost	Findings suggest self-efficacy, facilitating conditions, effort expectancy and performance expectancy to influence users' behavioral intention to adopt mobile health services, with age and gender acting as moderators.
(Kenny & Connolly, 2017)	Structural Equation Modeling with AMOS	247 from Ireland, and 202 from the US	Performance expectancy and social influence from UTAUT plus mHealth Self-Efficacy, Healthcare Need, and Health Status	The model explained 65.5% of the variance in adoption intention for the whole sample. The mHealth self-efficacy and health status did not present a significant effect on the intention to adopt mHealth.
(Hoque & Sorwar, 2017)	Partial Least Squares (PLS) Path Analysis	274 Bangladeshi individuals	UTAUT plus technology anxiety, and resistance to change	The study determined that performance expectancy, effort expectancy, social influence, technology anxiety, and resistance to change have a significant impact on the users' behavioral intention to adopt mHealth services. Conversely, facilitating condition revealed having no significant relation with behavioral intention to use mHealth.
(Ravangard, Kazemi, Zaker Abbasali, Sharifian, & Monem, 2017)	Partial Least Squares (PLS) Path Analysis	170 Iranians	Hedonic motivation, price value, and habit of the UTAUT2 plus usability, and ability, the use the technology	The findings suggest that price value, hedonic motivation, habit, and usability have a significant influence on the intention to use mHealth portals.
(Macedo, 2017)	Partial Least Squares (PLS) Path Analysis	278 Portuguese older adults	UTAUT2	Results confirm that most UTAUT2 predictors, some of them directly (behavioral intention, habit) and others indirectly (performance expectancy, effort expectancy, social influence, facilitating conditions, hedonic motivation).
(Quaosar, Hoque, & Bao, 2018)	Partial Least Squares (PLS) Path Analysis	245 Bangladeshi individuals	UTAUT plus perceived credibility	Findings indicate that performance expectancy, effort expectancy, social influence, and perceived credibility significantly influence the elderly's intention to use mHealth services. Facilitating conditions has no significant influence.
(Jewer, 2018)	Partial Least Squares (PLS) Path Analysis	118 Canadians	UTAUT	The results show significant effects in performance expectancy and facilitating conditions on behavioral intention to use an emergency department wait-times website, while the effort expectancy impact was not found significant.
(Nisha, Iqbal, & Rifat, 2019)	Partial Least Squares (PLS) Path Analysis	927 Bangladeshi individuals	UTAUT plus system quality (system reliability, system efficiency, system privacy), information quality, interaction quality (responsiveness, assurance, empathy), personal innovativeness, anxiety, perceived credibility, perceived self-efficacy, perceived financial cost, health-care knowledge, and trust.	Facilitating conditions was found to be the strongest direct determinant in influencing behavioral intention of mHealth services adoption. Additionally, effort expectancy, facilitating conditions, performance expectancy, and trust were also statistically found to be predictors of the behavioral intention to use mHealth

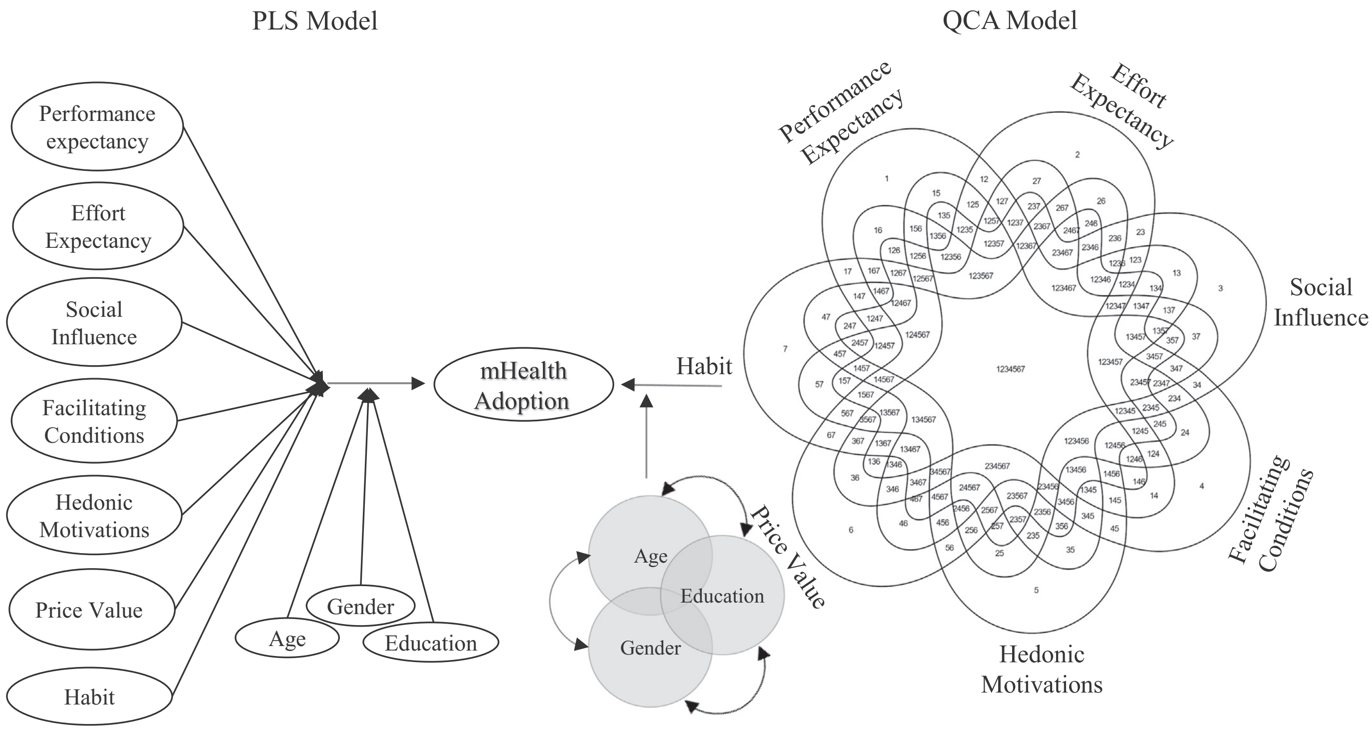

Fig. 1. Proposed PLS and QCA conceptual models.

measurement instrument was pre-tested on a group of university post-graduate students (nearly 20) to assess the clarity of meaning and comprehensiveness of the questions, as well as the structure of the questionnaire and the time needed to complete it. After some iterations of item editing and refinement, a team of three researchers undertook a rigorous content analysis to identify potential overlapping among the final set of items having as a reference each theoretical construct. Finally, a structured online questionnaire was designed using LimeSurvey 2.73 and distributed to a large population of mHealth users.

It is relevant to notice that the process of obtaining a full list of mHealth users proved to be cumbersome. Hence, consistent with numerous studies undertaken in this field of research, the survey was applied to a convenience sample of potential mHealth users. Invitation messages were sent to selected respondents in December 2018 through the messaging function and online message boards of potential users. A total of 120 respondents using mHealth devices and applications completed the structured questionnaire.

Concerning the respondent profile, 73% are female, nearly 83% have between 18 and 39 years old, suggesting that the young population are more prone to use the technology. Fifty-four percent are single and nearly 72% of the users have a graduate and post-graduate education degree. The items included in each dimension are depicted in the Appendix. Each item was measured on a 7-point Likert scale, where 1 denoted “Strongly disagree” and 7 denoted “Strongly agree”.

3. Data analysis and results

3.1. PLS analysis

Data were analyzed using both the Partial Least Squares (PLS) method with Smart PLS 3.2.8 (Ringle, Wende, & Becker, 2015) and the fsQCA 3.0 software (Ragin, 2017). The PLS path modeling is a structural equation method based on Ordinary Least Squares (OLS) which is performed in two steps: 1) the analysis of the measurement model and 2) the analysis of the structural model. The first step addresses the assessment of the validity and reliability of the measures. The Appendix depicts the factor loading and the reliability indicators, namely the Composite Reliability and the Cronbach's alpha whose values are greater than the threshold of 0.70 (Hair, Hult, Ringle, & Sarstedt, 2017). All the average variance extracted (AVE) values exceed 0.50 (Fornell & Larcker, 1981; Hair et al., 2017) supporting convergent validity. With few exceptions, which do not compromise the integrity of the constructs, nearly all factor loadings exceed the 0.707 threshold (see Appendix). Discriminant validity was assessed by applying the Fornell-

Table 2
Reported effect of UTAUT2 dimensions on mHealth.

Dimension	Significant effect	Non-significant effect
Performance expectancy	(Cimperman et al., 2016; De Veer et al., 2015; Dzimiera, 2017; Hoque & Sorwar, 2017; Jewer, 2018; Macedo, 2017; Quaosar et al., 2018)	(Boontarig et al., 2012)
Effort expectancy	(Boontarig et al., 2012; Cimperman et al., 2016; De Veer et al., 2015; Hoque & Sorwar, 2017; Idrish et al., 2017; Macedo, 2017; Quaosar et al., 2018)	(Dzimiera, 2017; Hsu et al., 2013; Jewer, 2018)
Social influences	(Hoque & Sorwar, 2017; Macedo, 2017; Moon & Hwang, 2016; Quaosar et al., 2018)	(Boontarig et al., 2012; De Veer et al., 2015)
Facilitating conditions	(Boontarig, 2016; Boontarig et al., 2012; Cimperman et al., 2016; Dwivedi et al., 2016; Idrish et al., 2017; Jewer, 2018; Moon & Hwang, 2016; Nisha et al., 2019)	(Hoque & Sorwar, 2017; Quaosar et al., 2018)
Hedonic motivation	(Gao et al., 2015;Macedo, 2017 ; Ravangard et al., 2017)	(Dwivedi et al., 2016)
Price value	(Boontarig, 2016; Boontarig et al., 2012)	(Macedo, 2017)
Habit	(Macedo, 2017; Ravangard et al., 2017)	

Table 3
Discriminant validity.

	Fornell-Larcker											HTMT									
Constructs	1	2	3	4	5	**6**	**7**	**8**	9	10	11	1	2	3	4	5	6	7	8	9	10
1.AmH	0.81																				
2.EE	0.32	0.84										0.34									
3.FC	0.43	0.67	0.75									0.45	0.75								
4.HM	0.43	0.24	0.17	0.82								0.46	0.25	0.20							
5.HT	0.50	0.15	0.22	0.30	0.80							0.56	0.31	0.32	0.36						
6.PE	0.70	0.36	0.52	0.23	0.38	0.87						0.75	0.36	0.53	0.23	0.39					
7.PV	0.12	0.35	0.25	0.27	0.12	0.08	0.80					0.08	0.40	0.31	0.19	0.14	0.07				
8.SI	0.29	0.15	0.27	0.20	0.28	0.21	0.25	0.93				0.31	0.16	0.31	0.20	0.31	0.22	0.27			
9.Edu	0.54	0.17	0.32	0.24	0.33	0.37	0.10	0.19	1.0			0.57	0.16	0.33	0.25	0.38	0.38	0.06	0.20		
10.Age	0.01	−0.06	−0.03	0.02	0.16	0.05	0.05	−0.05	−0.03	1.0		0.02	0.07	0.09	0.05	0.17	0.05	0.08	0.05	0.00	
11.Gend	−0.04	0.23	0.09	0.06	0.13	−0.03	−0.02	−0.04	0.10	0.13	1.0	0.05	0.26	0.09	0.08	0.17	0.05	0.03	0.03	0.10	0.13

Legend: AmH (Adoption of mHealth); EE (Effort expectancy); FC (Facilitating conditions); HM (Hedonic motivations); HT (Habit); PV (Price value); SI (Social Influence); Edu (Education); Notes: The diagonal in Fornell-Larcker shows the square root of the AVE.

Larcker criterion and the new Heterotrait-Monotrait Ratio of Correlations (HTMT) strictest threshold of 0.85 (Hair et al., 2017; Henseler, Ringle, & Sarstedt, 2015). Concerning the former, the square root of the AVE in the diagonal are higher than the off-diagonal elements in the corresponding rows and columns. Regarding the HTMT criterion, the obtained values are compared to a predefined threshold, which may vary between 0.85 (the strictest value) and 0.95. In both cases, the results suggest that all constructs are valid and reliable (Table 3).

Having ensured the reliability and validity measures, the structural relations were analyzed. The PLS-path analysis results (Table 4) show that performance expectancy, hedonic motivation, and habit are the significant direct predictors of mHealth adoption ($p < 0.05$) within the current sample data.

To retain consistency with Venkatesh et al. (2012) we have included three control variables (age, gender, and education) on the mHealth adoption. Education is used as a proxy for the original experience from the UTAUT2 model. After the inclusion of the control variables, no significant changes were observed for the influence of the UTAU2 dimensions. From the three control variables, only the level of education shows a significant positive effect on mHealth adoption ($\beta = 0.25$; $t = 4.11$).

3.2. Fuzzy-set qualitative comparative analysis

A fuzzy-set Qualitative Comparative Analysis (fsQCA) was performed to assess the propositions. The fsQCA method has attracted the attention of researchers in several fields of research and its use has been consistently growing since 2007 (Roig-Tierno, Gonzalez-Cruz, & Llopis-Martinez, 2017). To run the fsQCA data must be converted from the original 7 point- Likert scale into a dataset suitable for calibration. The process of converting included the following: 1) calculate the average scores of each construct, based on the respondents' responses and corresponding factor loadings; 2) calibrate the resulting data based on the percentile of the average score for each construct (Ragin, 2006). The calibration criteria adopted in the current study considered three anchors i.e., observations falling in the percentile-3 (e.g. 0.75) were assigned to the group of full membership; observations falling in the percentile-1 (e.g. 0.25) were assigned to the full non-membership group. Finally, the crossover point (0.50) is defined by the median. To assure comparability with the PLS the fsQCA analysis was conducted also with and without the demographic variables. Table 5 displays the descriptive statistics for the outcome and the antecedent conditions belonging to the UTAUT2 framework and the demographic variables (education, age, and gender).

As QCA assumes complex causality and focuses on asymmetric relationships, it requires the analysis of necessary, and sufficient conditions to produce the outcome (e.g. mHealth adoption). According to Schneider and Wagemann (2010), a condition is necessary when its consistency score is equal to or above 0.90. Since the highest consistency value among all conditions is 0.785, none of the variables, when considered solely, fulfill the request to be classified as a necessary condition to mHealth adoption (Table 6). Therefore, none of the seven UTAUT dimensions are by itself necessary to influence mHealth adoption and by that supporting Proposition 1.

The fsQCA results on the UTAUT2 dimensions suggest that these configurations are all sufficient, but no single condition is by itself necessary, meaning that no causal antecedent alone explains the adoption of mHealth. Therefore, it can be concluded that the data support Proposition 2 (see Table 7). Since no single condition seems to be necessary by itself, we proceed by testing groups of two conditions based on the results of the PLS analysis. Three disjunctions ("OR") were tested (Table 4), namely: PE + HT; PE + HM; HT + HM. Of these, the

Table 4
Effects on endogenous variables (direct effects).

Effects on endogenous variables	Expected Sign	Direct effect	t-Value	Percentile 95% - CI
Performance expectancy(PE) → mHealth adopt	+	0.45***	6.05	[0.332;–0.579]
Effort expectancy (EE) → mHealth adopt	+	0.08	1.01	[−0.044;–0.234]
Social influence (SI) → mHealth adopt	+	0.05	0.80	[−0.056;–0.177]
Facilitating conditions (FC) → mHealth adopt	+	−0.01	0.09	[−0.178–0.130]
Hedonic motivation (HM) → mHealth adopt	+	0.21***	2.96	[0.104–0.336]
Price value (PV) → mHealth adopt	+	−0.06	0.94	[−0.193–0.040]
Habit (HT) → mHealth adopt	+	0.18**	2.55	[0.070–0.292]
Education → mHealth adopt	+	0.25***	4.11	[0.160–0.361]
Age → mHealth adopt	+	−0.01	0.00	[−0.11–0.094]
Gender → mHealth adopt	+/−	−0.10	1.67	[−0.209–0.00]

Based on t(4999); *$p < 0.05$; t(0.05;4999) = 1.645; **$p < 0.01$; t(0.01,4999) = 2.327;***$p < 0.001$; t(0.001;4999) = 3.092; †bias-corrected and accelerated (BCa) BCI; one-tailed.

Table 5
Descriptive statistics of the outcome and antecedent conditions (calibrated).

	Variables*	Coding	Mean	Std. Dev.	Min	Max
Outcome	Adoption of mHealth	AmH	0.51	0.41	0.00	1
Antecedent	Performance expectancy	PE	0.51	0.41	0.00	1
Conditions	Effort expectancy	EE	0.47	0.39	0.00	1
	Social influence	SI	0.50	0.39	0.00	1
	Facilitating conditions	FC	0.48	0.41	0.00	1
	Hedonic motivations	HM	0.49	0.40	0.00	1
	Price value	PV	0.59	0.41	0.00	1
	Habit	HT	0.50	0.41	0.00	1
	Education	EDU	0.52	0.37	0.00	1
	Age	AGE	0.38	0.34	0.00	1
	Gender	GENDER	0.62	0.19	0.00	1

Table 6
Analysis of necessary conditions.

Outcome variable					
mHealth Adoption (**Amhi**)			Negation of mHealth Adoption (~**Amhi**)		
Conditions tested	Consistency	Coverage	Conditions tested	Consistency	Coverage
PE	0.785	0.790	PE	0.336	0.318
~PE	0.322	0.340	~PE	0.778	0.773
EE	0.619	0.668	EE	0.434	0.441
~EE	0.482	0.475	~EE	0.673	0.624
SI	0.672	0.687	SI	0.442	0.424
~ SI	0.437	0.454	~ Isi	0.674	0.659
FC	0.660	0.705	FC	0.381	0.382
~ FC	0.422	0.420	~ FC	0.706	0.661
HM	0.684	0.713	HM	0.381	0.373
~ HM	0.399	0.407	~ HM	0.707	0.677
PV	0.559	0.587	PV	0.500	0.494
~ PV	0.519	0.525	~ PV	0.582	0.553
HT	0.713	0.734	HT	0.382	0.369
~HT	0.387	0.400	~HT	0.726	0.704
Age	0.424	0.568	Age	0.444	0.559
~Age	0.671	0.562	~Age	0.656	0.517
Gender	0.732	0.608	Gender	0.694	0.543
~Gender	0.450	0.610	~Gender	0.499	0.636
Educ	0.580	0.570	Educ	0.571	0.528
~Educ	0.521	0.564	~Educ	0.536	0.545

Table 7
Configurations that lead to Adoption of mHealth (Amhi).

	Solutions					
Configuration	1	2	3	4	5	6
Performance expectancy(PE)	●	●	●	●	●	●
Effort expectancy (EE)	●	●	●	○	○	○
Social influence (SI)	●			●	○	○
Facilitating conditions (FC)	●	●	○	●	●	○
Hedonic motivation (HM)			●	●	○	●
Price value (PV)		○	●	●	○	○
Habit (HT)	●	○	●	●	●	●
Consistency	0.975	0.958	0.961	1.000	0.951	0.936
Raw coverage	0.266	0.113	0.105	0.060	0.066	0.078
Unique coverage	0.165	0.047	0.038	0.020	0.021	0.021
Overall solution consistency	0.965					
Overall solution coverage	0.454					

Note: black circles (●) indicate presence; white circles (○) denote negation; blank spaces denote absence; * This analysis is based on the Intermediate Solution.

first two disjunctions show a consistency score above 0.90. This suggests that Performance Expectancy (PE) plus Habit (HT), and Performance Expectancy (PE) plus Hedonic Motivation (HM) are by themselves necessary conditions guiding mHealth adoption.

The truth table was created to represent all logically possible combinations of causal (or antecedent) conditions that can lead to a specific outcome (mHealth). To simplify the configurations that lead to the outcome the Quine-McCluskey algorithm (Quine, 1952) for minimization of Boolean functions was employed confirming that the adoption of mHealth can be simplified to a more parsimonious configuration (Ragin, 2009).

To get a thorough understanding of the effect of the UTAUT2 conditions on the mHealth adoption the effect of the seven UTAUT2 dimensions were firstly considered alone in the fsQCA and later jointly with the demographic variables. Table 7 shows the possible configurations when using only the seven UTAUT2 dimensions on fsQCA. The overall solution consistency is 0.965 (standard threshold: 0.80) and the overall solution coverage is 0.454 (standard threshold: 0.45). The consistency represents the degree to which one condition (or combination of conditions) is a subset of another or the percentage of causal configurations of similar composition which result in the same outcome, while the coverage determines the empirical relevance of the same consistent subset (Ragin, 2006). Since both criteria are within the advisable threshold values (Table 7), this approach is considered suitable. In addition, the raw coverage describes the amount of the outcome that is exclusively explained by a certain alternative solution, while the unique coverage depicts the amount of the outcome that is unique to a path (Ragin, 2006), therefore, solution 1 presents itself as the best solution.

Examining the six different solutions (or causal paths) that lead the adoption of mHealth, it can be witnessed that in all cases the consistency scores are above 0.90, denoting that the data adjust well to all configurations. In addition, the existence of multiple solutions presented as sufficient for the adoption of mHealth implies the presence of equifinality (Fiss, 2011).

The demographic variables were then included in the fsQCA analysis with all the seven UTAUT2 dimensions. The results show that the solution - AmH = f (PE, EE, SI, FC, HM, VP, HT, age, gender, education) - did not conform with the overall solution coverage minimum threshold of 0.45, thus it was discarded. The demographic variables were then considered together with solution 1 (PE*EE*SI*FC*HT) from Table 7, providing an acceptable configuration.

Table 8 shows the configurations with the demographic variables. According to the first configuration (1), 16.4% of mHealth adopters simultaneously value performance expectancy (PE), effort expectancy (EE), social influence (SI), facilitating conditions (FC), and Habit (HT), jointly with gender (female). According to the second configuration, 8.4% of mHealth adopters value effort expectancy (EE), social influence (SI), facilitating conditions (FC), and Habit (HT). In terms of demographics, gender (female) and education (higher) are also relevant in this configuration. Finally, the third configuration indicates that 8.9% of mHealth adopters value performance expectancy (PE), effort expectancy (EE), facilitating conditions (FC), and Habit (HT). In this configuration, age (young adults), gender (female), and education (higher) are all relevant for mHealth adoption.

Additionally, to assess if particular models of age, education, and gender have high consistencies in indicating the complex solution models, a fuzzy statement score was computed for the cases for each of

Table 8
Analysis of sufficient conditions including demographic variables.

	Raw coverage	Unique Coverage	Consistency
PE*EE*SI*FC*HT*~AGE*GENDER*~EDUC	0.164	0.100	0.983
~PE*EE*SI*FC*HT*~AGE*GENDER*EDUC	0.084	0.032	0.833
PE*EE*~SI*FC*HT*AGE*GENDER*EDUC	0.089	0.045	0.926
Overall Solution coverage: 0.250			
Overall Solution consistency: 0.914			

the first three solutions. Consequently, the models become the outcomes for the complex antecedent conditions of demographic variables. The results show that none of the causal conditions (age, education, and gender) is by itself necessary since consistency scores ranged from 0.404 to 0.706, below the minimum threshold. Groups of conditions were also tested for necessity and although age + education present an adequate level of consistency for the solutions (0.925, 0.915, 0.914) they are not sufficient according to sufficiency analysis (consistency = 0.444, 0.445, 0.473). Regarding the sufficiency evaluation for single conditions, three models were assessed based on the general model: Solution(i) = f (age, gender, education), where $i = 1,2$, and 3. In the three cases, the best solution found by fsQCA was ~gender*~educ and age*~gender. The overall solution consistency level for the three models assessed, which indicates the combined consistency of the causal recipes, are low (0.521, 0.520, and 0.558) and well below the recommended acceptance level (> 0.80), meaning that age, education, and gender do not consistently indicate any of the three complex solution models.

Contrasting PLS and fsQCA results it can be noticed that there are similarities between the two, namely on the central role of PE but also on the global prominence of HM and HT. The PLS-SEM solution depicted in Table 4 indicates that three out of the seven UTAUT2 dimensions are significant predictors for mHealth adoption. Among these, special emphasis is attributed to performance expectancy (β = 0.45), hedonic motivation (β = 0.21) and habit (β = 0.18). These same findings can be found using fsQCA, although mixed with other conditions (or antecedents). However, the results from fsQCA confirm that none of the seven UTAUT2 dimensions are necessary just by itself to explain mHealth adoption (confirming proposition 1). Among the demographic variables, only education is relevant (β = 0.25) for the adoption of mHealth.

When trying to assess if the UTAUT2 dimensions are by themselves sufficient to influence mHealth adoption, Table 7, show that although six solutions are pointed by fsQCA, solutions 1 and 2 deserve special attention due to the significance of the consistent scores, raw coverage, and unique coverage. These solutions can be represented using the symbol "*" to denote the logical operator AND, and the symbol "~" to the negation of the condition. Accordingly, the first configuration (solution 1) combines five conditions and can be represented as PE*EE*SI*FC*HT, where the next best solution (solution 2) can be represented by PE*EE*FC* ~PV*~ HT. It is interesting to notice that this last solution is similar to solution 1, except for the price value and habit conditions. Regarding solutions 3 and 4, it is worthy to highlight these are not the best solutions but are the ones that best incorporate PLS-SEM results as both include the three significant OLS factors (performance expectancy, hedonic motivation, and habit). In terms of the demographic variables, gender and educations stand out.

4. Conclusions and implications

The purpose of this investigation was to assess the configurations of UTAUT2 that explain the adoption of mHealth. By using a mixed-methods approach that combines Partial Least Squares (SEM-PLS) with fuzzy-set qualitative comparative analysis (fsQCA) to answer the central research question, this study takes a step forward in the research field of mHealth adoption. Although PLS-SEM is capable to offer an answer based on the net effect of a single variable on mHealth adoption, the use of fsQCA allows understanding that alternative solutions based on the combination of UTAUT2 dimensions are equally capable of explaining mHealth adoption.

There are several conclusions and implications that can be drawn from the results. At the theoretical level, the fsQCA results indicate that no single condition is necessary by itself to explain mHealth adoption. Considering the six configurations produced by fsQCA, without the demographic variables, no UTAUT2 dimension by itself is either necessary or sufficient to achieve the outcome. This suggests that the adoption of mHealth results from a mix of several conditions, in which performance expectancy assumes particular importance as it is present in all configurations. This finding is consistent with previous studies by Cimperman et al. (2016), Hoque and Sorwar (2017), Jewer (2018), Nisha et al. (2019), and Quaosar et al. (2018) among others and stresses the need for the players in the market to adopt a multidimensional approach when designing mHealth offers with special focus on finding the perfect mix for each market segment but always anchored on performance expectancy.

It is interesting to notice that, performance expectancy is also the best predictor for mHealth adoption in the PLS analysis, confirming that both approaches produce equivalent findings. Since facilitating conditions is present in the two fsQCA solutions jointly with performance expectancy and effort expectancy, the market players must acknowledge that the perception of the usefulness of mobile health devices and applications to better control, monitoring and increase health condition is critical to new adopters. In fact, previous studies (e.g. Dzimiera, 2017; Idrish et al., 2017; Nisha et al., 2019) suggest that new adopters are especially sensitive to performance expectancy, effort expectancy, social influence, facilitating conditions and habit, which taken together are sufficient to foster the adoption of mHealth. According to the fsQCA results, demographic characteristics seem also to affect the adoption of mHealth, namely young and well-educated people, as well as women are more prone to adopt mHealth, although only education appears as significant in the PLS solution.

The comparison between fsQCA and PLS-SEM approaches shows that both methods are complementary and can be used together to improve the range and depth of the solutions available to decision-makers to better address different adopters' profiles. By restraining the set of significant predictors to performance expectancy, hedonic motivation and Habit PLS-SEM solution provides decision-makers with an incomplete picture of the phenomenon since these factors, when taken alone, do not capture all dimensions of mHealth adoption behavior because exclusively positive or negative relations between single variables are not supported by all cases in any dataset (Woodside, 2013). As fsQCA considers combinations of causal relations instead of independent effects, it provides a complementary and more comprehensive view of the reality under study. This is particularly important from a managerial perspective. For example, in the best solution obtained from fsQCA (Solution 1), some of the conditions were not significant in PLS-SEM estimation but fsQCA points that when considered together with other conditions, it can lead to mHealth adoption. This situation was confirmed by testing groups of two conditions. The findings are that Performance Expectancy (PE) plus Habit (HT), and Performance Expectancy (PE) plus Hedonic Motivation (HM) are actually necessary conditions for mHealth adoption.

In summary, it can be concluded that the adoption of mHealth is indeed a complex phenomenon since several product characteristics, users' psychological dimensions and demographic characteristics dynamically interact to produce the desired behavior. Therefore, a multimethod approach by combining fsQCA analysis and PLS-SEM is a valuable analytical tactic to investigate the complex causality behind mHealth adoption, helping beating potential limitations and shortcomings associated with conventional statistical ordinary least squares regression-based methods. For practitioners concerned with increasing mHealth adoption, the findings provide a basis for the development of market strategies, which should be centered on performance expectancy, facilitating conditions, and habit as core dimensions, especially targeting well-educated young females.

5. Limitations and future research

This study is not without limitations. For example, the proposed conceptual model considers solely the UTAUT2 dimensions proposed by Venkatesh et al. (2012). The UTAUT2 dimensions are still very technological oriented, however other dimensions that might lead to mHealth adoption are not present in the UTAUT2 framework (e.g. health literacy, health condition, privacy perception, among others) should also be considered. The interpretation of the findings and their generalization deserve also a note of caution due to the nature and size of the sample.

This study can be further extended by adopting a perspective similar to the one by Mas-Tur, Pinazo, Tur-Porcar, and Sánchez-Masferrer (2015) focused on the negation of the outcome condition to explore what to avoid in order to achieve success on the adoption of mobile health.

Finally, in terms of future research, one important step would be to conduct more extensive research to categorize the profiles of mHealth adopters and try to match each profile with a particular configuration of conditions to improve the acceptance and adoption rate of mHealth solutions.

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Declarations of interest

None.

Appendix A. Measurement model

CONSTRUCT / Dimension /Item	Factor Loadings	t-test
Adoption of mHealth - CR = 0.92; CA = 0.90; AVE = 0.67]		
AmH1. I am determined to use a mobile health application to monitor my health in my daily life.	0.76	10.8
AmH2. I intend to use a mobile health application to monitor my health.	0.86	27.3
AmH3. I foresee to use a mobile health application to monitor my health in the future.	0.85	25.9
AmH4. I'm curious about using a mobile health application to monitor my health.	0.78	15.1
AmH5. I find it would be good to use a mobile health application to monitor my health.	0.84	24.8
AmH6. I evaluate as positive the use of a mobile health application to monitor my health.	0.81	19.8
UTAUT		
Performance expectancy - CR = 0.95; CA = 0.93; AVE = 0.76]		
ED1. I find mobile health applications useful in my daily life.	0.86	36.6
ED2. Using mobile health applications increases my chances of achieving things that are important to me.	0.87	39.4
ED3. Using mobile health applications helps me to control activities more quickly.	0.82	14.9
ED4. Using mobile health applications increases my effectiveness in monitoring my health.	0.91	61.5
ED5. Using mobile health applications increases my performance in monitoring my health.	0.87	26.7
ED6. Using mobile health applications increases the facility in monitoring my health.	0.88	40.8
Effort expectancy - CR= 0.92; CA= 0.89; AVE= 0.70]		
EE1. Learning how to use mobile health applications is easy for me.	0.88	18.9
EE2. My interaction with mobile health applications is clear and understandable.	0.90	17.7
EE3. I find mobile health applications easy to use.	0.85	11.0
EE4. It is easy for me to become skillful at using mobile health applications.	0.85	16.1
EE5. Using mobile health applications does not require me much effort.	0.68	6.15
Social Influence - CR = 0.97; CA = 0.96; AVE = 0.86]		
SI1. People who are important to me think that I should use mobile health applications.	0.94	39.9
SI2. People who influence my behavior think that I should use mobile health applications.	0.95	47.0
SI3. People whose opinions that I value prefer that I use mobile health applications.	0.95	52.9
SI4. People who are important to me agree with the use of mobile health applications.	0.85	16.2
SI5. People I trust believe that I should use mobile health applications.	0.94	45.9
Facilitating Conditions - CR = 0.88; CA = 0.84; AVE = 0.56]		
FC1. I have the necessary resources to use mobile health applications	0.59	4.20
FC2. I have the knowledge necessary to use mobile health applications.	0.75	11.8
FC3. Mobile health applications I use is compatible with other technologies.	0.76	15.0
FC4. I can get help from others when I have difficulties using mobile health applications.	0.65	7.05
FC5. I feel comfortable using mobile health applications.	0.88	36.8
FC6. I have not problems to use mobile health applications.	0.84	20.8
Hedonic Motivation - CR = 0.93; CA = 0.92; AVE = 0.67]		
HM1. Using mobile health applications is fun.	0.82	21.4
HM2. Using mobile health applications is enjoyable.	0.75	12.8
HM3. Using mobile health applications is very entertaining.	0.72	10.9
HM4. Using mobile health applications give me pleasure.	0.82	19.4
HM5. Using mobile health applications is exciting.	0.90	33.3
HM6. Using mobile health applications is thrilling.	0.85	19.8
HM7. Using mobile health applications is delightful.	0.86	28.0

Price Value - CR = 0.88; CA = 0.90; AVE = 0.65]		
PV2. Mobile health applications are a good value for the money.	0.97	3.59
PV3. Mobile health applications offer the amount corresponding to the money you pay.	0.88	3.48
PV4. I find economical using mobile health applications.	0.67	2.44
PV5. Irrespective of price Mobile health applications are always a good deal.	0.65	2.56
Habit - CR = 0.83; CA = 0.73; AVE = 0.64]		
HT1. The use of mobile health applications has become a habit for me.	0.92	52.5
HT2. I am addicted to using mobile health applications.	0.55	3.94
HT4. Using mobile health applications has become natural to me.	0.88	24.5

CR = Composite Reliability; CA = Cronbach Alpha; AVE = Average Variance Extracted; Based on t(4999); *$p < 0.05$; t(0.05;4999) = 1.645; **$p < 0.01$; t(0.01;4999) = 2.327;***$p < 0.001$; t(0.001;4999) = 3.092; one-tailed.

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