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Usage intensity of mobile medical apps: A tale of two methods☆

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ABSTRACT

Web 2.0 technologies have changed the traditional relationship model between doctors and third parties, and a plethora of apps are now available for the medical profession. This study presents unpublished findings about the potential drivers that currently influence mobile medical app usage intensity. Logistic regression and fuzzy-set qualitative comparative analysis (fsQCA) are both used to examine usage intensity. By using two research methods, rather than just one, the findings are greatly enhanced. Logistic regression results show that high usage intensity is explained by high perceived usefulness and high perceived ease of use. FsQCA, on the other hand, highlights that the combinations of multiple conditions are also significant, leading to the finding that low mobile medical app usage intensity is associated with low perceived ease of use, high perceived usefulness, low peer influence, high seniority, and younger female doctors.

1. Introduction

The health sector is extremely complex and heavily regulated. A range of activities is used to market the pharmaceutical industry, including direct contact with prescribers, specialized magazines, electronic mail, and direct advertising to the final consumer. All of these activities are profoundly regulated by both national and international legislation, which, for example, does not authorize the pharmaceutical industry to directly promote prescription drugs to consumers. Alkateeb and Doucette (2009) confirm that the competition for the length of time of contact with a doctor is intense, obliging salespersons to find alternative channels. It is no surprise that interest in the Internet as a tool for health information and communication has grown considerably in recent years (Korp, 2006). As empirical evidence of this trend, note that 40,000 healthcare apps were available in the U.S. Apple iTunes store in 2015 (Silva, Rodrigues, de la Torre Díez, & López-Coronado, 2015).

Web 2.0 challenges the traditional communication model, and it can, therefore, be said to significantly change the way communication is conducted in this area (Chou, Prestin, Lyons, & Wen, 2013). Bullock (2014) argues that these tools can facilitate the sharing of knowledge, values, and expectations throughout the medical community. With the increase in use of smartphones and apps by the medical community (Franko & Tirrell, 2012), mobile-health has become an indispensable tool for communication in the health sector (Ventola, 2014), with professionals benefitting from greater convenience, precision, efficiency, productivity, and cutting-edge technology, resulting in even better clinical decision-making. Clinical practice has been transformed using these devices, due to the need for better communication resources and information in healthcare locations, as well as omnipresence (Bullock, 2014; Ventola, 2014). Wendy (2016) concludes that health organizations and health professionals from France, the UK, and the USA are increasingly using mobile applications.

Mobile health success depends heavily on its adoption by the medical profession (Gagnon, Ngangue, Payne-Gagnon, & Desmartis, 2016). Arguably, all these professionals possess mobile apps installed on their mobile devices. However, this does not necessarily mean that they use the apps frequently. Considering both the communication restrictions experienced by the pharmaceutical industry and the ongoing debate regarding the advantages of mobile health, there is a need to assess the factors that enable medical mobile apps usage by the medical profession.

Research regarding the motivational factors that lead to the adoption and usage of health apps by professionals is expanding (Gagnon et al., 2016; Kwon, Mun, Lee, McLeod, & D'Angelo, 2016; Silva et al., 2015), but is still scarce regarding the impact of certain individual factors – peer influence, seniority, and demographic characteristics. This scarcity raises the research question: Which factors or configurations of factors drive mobile medical app (MMA) usage intensity in the medical profession? This paper addresses this question using both logistic regression (LR) and fuzzy-set qualitative comparative analysis (fsQCA). Ordanini, Parasuraman, and Rubera (2014) and Grohs, Raies, Koll, and Mühlbacher (2016) argue that single antecedent conditions are rarely necessary or sufficient to predict an outcome. Furthermore, as Grohs et al. (2016) suggest, the configurations of factors that enable

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MMA usage intensity found by LR could be different from those found by fsQCA, as each method has its own perspectives and assumptions about data. Whereas LR shows one combination symmetric relationship between predictor variables and the outcome variable, fsQCA analyzes combinations of levels of predictor variables that lead to a higher level of outcome, in a potential asymmetric relationship. By using two research methods, rather than just one, the findings are enhanced (Woodside, 2015), contributing to a better understanding of the factors that influence usage intensity of MMAs. This paper also responds to QCA analysts' request to have their method included as part of a multi-method approach (Grendstad, 2007).

2. Mobile health-related app usage intensity

MMAs turn smartphones into useful tools for health practice (Mosa, Yoo, & Sheets, 2012). However, only limited research exists regarding the use of healthcare apps by doctors or medical students (Ozdalga, Ozdalga, & Ahuja, 2012). Previous research on MMA usage by doctors produced mixed results. Smartphones are already used regularly by doctors to perform their job (O'Connor et al., 2013), and they are becoming increasingly popular among medical students for mobile learning (Masika et al., 2015). Likewise, they are often used as drug guides and medical calculators (Franko & Tirrell, 2012). However, research also shows that the increasing penetration rate of smartphone ownership among doctors does not necessarily equate to higher usage of MMAs to support their clinical practice (Liu et al., 2016; Rung, Warnke, & Mattheos, 2014).

The existing literature shows that MMA research has focused largely on its effectiveness. MMA has been investigated in terms of its convenience and effectiveness in controlling obesity (Carter, Burley, & Nykjaer, 2013), modifying behaviors (Willems, Willemsen, & Nagelhout, 2013), and managing disease (Arsand, Tufano, & Ralston, 2008). Research is still scarce regarding the factors that promote MMA usage intensity among doctors.

Previous research identifies some causes for the adoption of new technologies. Davies, Kotadia, Mughal, Hannan, and Alqarni (2015) argue that the reliability of information, app security, and technical difficulties are important barriers to app usage. On the other hand, they observe that ease of use, reliability, security, regulated information, cost, fun, and impact on battery life are also ideal characteristics for an MMA. Similarly, Bidmon, Terlutter, and Röttl's (2014) study of patients in the USA and Germany highlights that perceived ease of use, age, and gender significantly affect the adoption of mobile physician-rating apps. Well before mobile apps existed, Davis (1989) asserted that the acceptance of new technologies depends on perceived utility and perceived ease of use. Orruño, Gagnon, Asua, and Abdeljelil (2011) argue that extrinsic factors, such as peer influence, condition the adoption of new technologies.

This study investigates the factors that are often associated with the adoption of new mobile technologies (see Gagnon et al., 2016, for a systematic review of mobile health adoption barriers and facilitators): perceived ease of use, perceived usefulness, and peer influence. Seniority, age, and gender are used as control variables.

2.1. Perceived ease of use

Perceived ease of use relates to the belief that using a technology is effortless (Davis, Bagozzi, & Warshaw, 1989; Tung, Chang, & Chou, 2008). Conversely, the more difficult it is to get information, the longer the adoption period will be (Alkateeb & Doucette, 2009). Gleason (2001) argues that doctors use e-detailings because they find them intuitive to use and easy to access. Kim and Chang (2007) and Gagnon et al. (2016) also defend the idea that perceived ease of use favors the adoption of technology in healthcare. In the same line of thought, a recent study of antecedents of mobile app usage among smartphone users (Kim, Yoon, & Han, 2016) shows that perceived ease of use positively influences app usage. On the contrary, Hur, Lee, and Choo (2017) found a significantly negative direct effect of perceived ease of use on innovative apps usage intention among millennial and mature consumers. However, they argue that, while ease of use does increase app usage intention, other emotion factors also contribute. Based on the above, the following proposition is posited:

P1.. *Perceived ease of use is positively associated with intensity of MMA usage.*

2.2. Perceived usefulness

Perceived usefulness is the degree of belief that using a technology enhances performance (Davis, 1989), and is therefore associated with efficiency and effectiveness (Tan & Teo, 2000). Many authors (e.g., Agarwal & Karahanna, 2000; Venkatesh & Davis, 2000; Wu & Wang, 2005) argue that perceived usefulness has a direct impact on usage intention. In a study more specifically related to health information on the Internet, Kim and Chang (2007) defend the idea that perceived usefulness is a key factor in accepting information technology. In the same line of thought, Hur et al. (2017) conclude that perceived usefulness has a direct impact on app usage intention. Gagnon et al. (2016) show that perceived usefulness is the most recurrent adoption factor for the adoption of mobile health. Considering these findings, this study postulates that:

P2.. *Perceived usefulness is positively associated with intensity of MMA usage.*

2.3. Peer influence

Fishbein and Ajzen (1975) define social influence as being the perception of what most people consider should or should not be done. Similarly, Venkatesh, Morris, Davis, and Davis (2003) consider social influence as the degree to which an individual perceives that it is important that others believe he or she should use a new technology. An extensive study in social psychology maintains that peer influence can indeed impact behavior (Gunther, Bolt, & Borzekowski, 2006). Xue, Yen, and Chang (2012) also conclude that subjective norms significantly predict adoption intentions for the use of info-health technologies. Alkateeb and Doucette (2009) defend the idea that doctors discuss with their peers the advantages and disadvantages of new technologies. Thus, the more doctors perceive peer norms as being supportive, the more likely they are to use MMA. Therefore, the following proposition is posited:

P3.. *Peer influence is positively associated with intensity of MMA usage.*

2.4. Seniority

There is a lack of research relating the use of MMA to seniority (i.e., comparing usage between medical students and fully-qualified doctors). One of the few available studies shows no differences between the two cohorts in terms of the ownership of health applications (Payne, Wharrad, & Watts, 2012). Furthermore, the groups show similar trends of using apps several times a day. Given the scant research available on the impact of seniority on MMA usage intensity, the following proposition is formulated:

P4.. *Seniority is positively associated with intensity of MMA usage.*

2.5. Age

The literature suggests that the older the doctor, the lesser the willingness to adopt new technologies. Alkateeb and Doucette (2009) note that younger doctors adopt new technologies if they were exposed to them during their training programs. Similarly, Patel et al. (2015) conclude that younger doctors are more likely than older doctors to use MMAs. To the contrary, a recent study by Veríssimo (2016) shows that there is no direct relationship between age and mobile app adoption. Drawing on the above arguments, the following proposition is suggested:

P5.. *Medical students are positively associated with MMA usage intensity.*

2.6. Gender

Payne et al. (2012) conclude that males and females own a similar number of smartphones, but males are significantly more likely to install apps. Similarly, Bidmon et al. (2014) conclude that males are more willing to pay for physician-rating apps. However, Bidmon and Terlutter (2015) defend the idea that women are typically more inclined to use the Internet for health-related information. In the same line of thought, a survey of medical students at the Leipzig Medical School (Sandholzer, Deutsch, Frese, & Winter, 2015) shows that the female gender has both higher general interest and higher perceived benefit of new technologies. Considering these dissimilar findings, this study suggests:

P6.. *Females are positively associated with MMA usage intensity.*

3. Data, measures, and methods

3.1. Data

The target population for this study consists of fully-qualified doctors and medical students. The survey, which was carried out in 2015, was sent by e-mail to a 6000-member medical social network (www.drshare.pt), resulting in 255 completed questionnaires. The final sample is composed of 199 respondents, all of whom have MMAs installed on their smartphones. The sample is composed of 165 fully-qualified doctors (113 internal medicine doctors and 52 medical specialists) and 34 unspecialized medical students. Approximately 62% of respondents are female, with no significant differences between medical students and qualified doctors. The younger group (under 30 years old) accounts for 50% of the sample, with more than two-thirds of medical students and internal medicine doctors falling in the 23 to 29 years old age interval. The older group (aged 30 years old or older), 78% of which are between 30 and 43 years old, accounts for the remaining 50% of the sample and includes mainly medical specialists and older internal medicine doctors. Finally, 64% of respondents use medical apps up to three times a week (low usage intensity group) and 36% use such apps more than three times a week (high usage intensity group).

3.2. Measures

The first section of the questionnaire recorded the subjects' professional seniority and information regarding their usage of MMAs. The second section asked the subjects to indicate their degree of agreement with a series of possible factors that might affect usage intensity. The items related to perceived ease of use and perceived usefulness were extracted and adapted from Tung et al. (2008). The item related to peer influence was adapted from Alkateeb and Doucette (2009). Before the final revisions, items that were translated to Portuguese were translated back into English, and the back-translation showed a strong equivalence. The questionnaire was pre-tested with three doctors to clarify the understanding of those items. The pre-test procedures resulted in minor adjustments to the layout and style of the questionnaire. Some items were eliminated, and others were modified to reduce ambiguity or duplication of meaning.

The final measurement instrument consisted of seven items that measured three factors: perceived ease of use, perceived usefulness, and peer influence. The usage intensity dependent variable (*usage*) was calculated based on the reply to the question "How often do you use MMAs?" Responses were split into two separate groups: "up to three times per week" and "more than three times a week." Three independent variables were measured using a five-point Likert scale, where 1 indicated "strongly disagree" and 5 indicated "strongly agree." Perceived ease of use (*peou*) is captured by two items ("I find that MMAs are very easy to use" and "I find that the human interface of MMAs is clear and easy to understand"). Perceived usefulness (*pu*) uses four items ("Using MMAs can improve my work efficiency," "Using MMAs would enhance my job performance," "Using MMAs would increase my productivity, and "I find MMAs useful for my work"). Finally, one item measures peer influence (*peer*) ("In my practice setting, most of the doctors are using MMAs"). The internal consistency is high. All factors exceed the recommended minimum Cronbach's alpha coefficient ($\alpha = 0.70$) (Nunnally, 1978): *peou* ($\alpha = 0.80$) and *pu* ($\alpha = 0.87$). Before the calibration of the variables, an index (score) was calculated for each factor by averaging the corresponding items. The study includes three control variables that can influence MMA usage intensity: age, seniority, and gender.

To address the issue of common method variance (Podsakoff, MacKenzie, Lee, & Podsakoff, 2003) that threatens fit validity, this study uses Harman's (1960) single-factor test. The Bartlett test of sphericity is significant ($\chi^2 = 590.7$, $p < 0.000$), showing that the sample data are suitable for the analysis. The three factors with an eigenvalue of > 1.0 account for 81% of variance. Next, an exploratory factor analysis is carried out, where all variables are loaded onto a single factor and constrained, so that there is no rotation (Podsakoff et al., 2003). The newly-introduced common latent factor explains only 46% of the variance. The items do not merge into one factor, and therefore the mono-method bias is not a serious problem.

3.3. Methods

Both fsQCA and LR are used to analyze the same data. By contrasting LR with fsQCA, this paper contributes to the ongoing debate about whether fsQCA performs better than other methods in accounting for causal complexity (Grendstad, 2007). Considering the divergence between fsQCA and LR in their accounting for causal complexity and procedures, somewhat divergent conclusions are foreseen.

FsQCA (fs/QCA 2.5 software package) uses Boolean algebra to construct comparisons among configurations of dependent variables (Ragin, 1987), the latter being used as basic elements of the different configurations. Cases are configurations of conditions instead of observations; causation is multiple and conjunctural. FsQCA is thus more focused on seeking patterns than on confirming or disconfirming hypotheses (Ragin & Bradshaw, 1991). Contrary to regression analyses, where researchers estimate the effect of independent variables on a dependent variable, fsQCA is used to identify the combinations of causes in a context, which is a limitation of traditional probabilistic statistical techniques (Fiss, 2011). As the analysis develops, complexity is reduced by identifying a small number of conditions that are necessary, sufficient, both, or neither.

Application of the fsQCA procedure starts by identifying cases of driver configuration for an outcome (Fiss, 2011; Ragin, 2008). This study uses important factors from the technology adoption literature. Accordingly, the truth table shows all combinations of presence or absence of enablers of MMAs (perceived ease of use, perceived usefulness, seniority, peer influence) and demographic variables (age and gender). Next, each case is characterized by its degree of membership for each case in a given causal recipe that explains the outcome, which in this case is MMA. Membership of both the outcome and each causal condition vary between 0.00 (full non-membership) and 1.00 (full membership) (Ragin, 2000). The original five-point Likert scale values of perceived ease of use, perceived usefulness, and peer influence are all

Table 1
Summary data for perceived ease of use, perceived usefulness, and peer influence.

Statistics	*Peou*	*Pu*	*Peer*
N (valid)	199	199	199
Mean	3.67	4.02	2.69
Std. error of mean	0.05	0.04	0.06
Median	4.00	4.00	2.00
Std. deviation	0.65	0.63	0.92
Minimum	2.00	1.80	1.00
Maximum	5.00	5.00	5.00
Calibration values at			
95%	5.00	5.00	4.00
50%	4.00	4.00	3.00
5%	2.50	3.00	2.00

Table 2
Overview of necessary conditions.

Condition	Mobile medical app usage intensity			
	High usage (usage)		Low usage (∼usage)	
	Consistency	Coverage	Consistency	Coverage
Peou	0.46	0.42	0.35	0.58
∼Peou	0.54	0.31	0.65	0.69
Pu	0.62	0.45	0.43	0.55
∼Pu	0.38	0.27	0.57	0.73
Peer	0.42	0.41	0.34	0.59
∼Peer	0.57	0.33	0.66	0.67
Seniority	0.89	0.38	0.80	0.62
∼Seniority	0.11	0.23	0.20	0.76
Age	0.48	0.34	0.51	0.66
∼Age	0.52	0.37	0.48	0.63
Gender	0.60	0.35	0.63	0.65
∼Gender	0.39	0.37	0.37	0.63

Note: ∼indicates the absence of a condition.

calibrated into a fuzzy-set scale, as recommended by Woodside (2013). The study uses three anchors for calibration of the fuzzy set: The original value that covers 5% of the data values is set as the point of full non-membership (fuzzy score = 0.05), the original value that covers 50% of the values is set as the cross-over point (fuzzy score = 0.50), and the original value that covers 95% of the values is set as the point of full membership (fuzzy score = 0.95). Table 1 provides the original values of these three points for perceived ease of use, perceived usefulness, and peer influence. The outcome is a dichotomous variable that distinguishes between health professionals who use MMAs intensively (usage), and those who do not (∼ usage). Seniority is a dichotomous condition which establishes whether the respondent is a medical student (coded as zero, outside the set), or a fully-qualified doctor (coded as one, fully in the set). Similarly, age is a dichotomous condition, coded zero when the respondent is < 30 years old, and one when the respondent is 30 or more years old. Finally, the gender of respondents is coded as zero for male and one for female.

The next step in applying fsQCA involves reducing configurations of factors to a simple logical expression that meets the recommended consistency and frequency thresholds. Consistency is similar to the significance test, indicating the degree to which a configuration is necessary to warrant an outcome. A coverage measure is also calculated for each final sufficient configuration, providing evidence of its relative empirical importance (Ragin, 2008). Ragin (2006) defends the proposition that causal conditions with consistency scores above 0.90 and coverage scores > 0.50 can be considered necessary for the outcome. Causal sufficiency exists when the consistency score is > 0.80 (Wu, Yeh, Huan, & Woodside, 2014). For the final configurations, the study selects the "intermediate solution" for interpretation. Schneider and Wagemann (2010) and Woodside (2014) argue that the outcome and the negation of the outcome should always be dealt with in two separate analyses. Therefore, this study first analyzes which conditions lead to the intensive usage of MMAs (*usage*). Subsequently, the analysis investigates the alternative model of low-intensity usage of MMAs (∼*usage*). FsQCA tests the following models:

$usage = f(peou, pu, peer, seniority, age, gender)$

$\sim usage = f(peou, pu, peer, seniority, age, gender)$

LR analysis is appropriate when the dependent variable is dichotomous. It is used to explain the relationship between the outcome and one or more nominal, ordinal, interval, or ratio-level independent variables. It adds, averages, and multiplies selected independent variables to calculate their impact on the dependent variable, with effects controlled against each other through statistical significance (Grendstad, 2007). LR does not assume that independent variables are distributed as a multivariate normal distribution. The conditional mean of the dichotomous variable should have a binomial distribution (Peng, Lee, & Ingersoll, 2002). LR results report the complete LR model, including the Y-intercept and odds ratios. No specific rules in terms of sample size apply to LR. Peng et al. (2002) recommend a minimum ratio of 10-to-1, with a minimum sample size of 100 or 50. With a sample of 199 respondents, the study meets the recommended threshold.

For LR analysis, MMA usage intensity is the dichotomous outcome, coded as zero for "up to three times a week" and as one for "more than three times a week." Three independent variables are based on strongly agree-strongly disagree five-point Likert items and measure perceived usefulness, perceived ease of use, and peer influence. Another three dichotomous independent variables measure seniority (coded as zero for medical students and one for qualified doctors), age (coded as zero for < 30 years old and one for 30 or more years old), and gender (coded as zero for male and one for female).

4. Results

The results of fsQCA in Table 2 show no condition with a consistency level above 0.90 and a raw coverage > 0.50, which would qualify the condition as necessary (Ragin, 2006). Regarding MMA high usage intensity (*usage*), the consistency scores range between 0.11 and 0.89. Low usage intensity (∼*usage*) of MMA consistency scores of 0.20 to 0.80 are observed. On their own, perceived ease of use, perceived usefulness, peer influence, age, and gender are neither necessary nor sufficient for high or low MMA usage intensity. Propositions 1, 2, 3, 5, and 6 are thus not supported. Seniority is a sufficient predictor of MMA usage intensity but not a necessary condition. Proposition 4 is supported. The high coverage levels of each enabler suggest the existence of multiple configurations of factors relating to MMA usage intensity.

Table 3 shows the fsQCA results of the sufficiency analysis for MMA high and low usage intensity. The intermediate solution for a high usage intensity outcome indicates that Models 1a and 1b do not achieve the minimum recommended consistency threshold of 0.80 needed to draw conclusions. High MMA usage intensity does not seem to be a systematic outcome of the measured enablers. To account for causal asymmetry (e.g., Fiss, 2011; Frösén, Luoma, Jaakkola, Tikkanen, & Aspara, 2016), this study also tests the relationship between the enablers and low MMA usage intensity. The resulting intermediate solution is highly consistent (0.86), with fair empirical importance (coverage = 0.11). The findings in Table 3 show that MMA low usage intensity can be achieved under three different complex configurations. One important path (2c) relating to low MMA usage intensity shows low perceived ease of use combined with high perceived usefulness, low peer influence, high seniority, and younger female doctors. The other two configurations show high consistency, but are empirically rare, with unique coverage rates of 0.03 or less.

In addition to studying fit validity, as discussed above, this study tests the predictive validity of configurations of enablers leading to low MMA usage intensity through cross-validation with two holdout

Table 3
Results of the intermediate solution.

	Mobile medical apps usage intensity				
	Outcome: High usage		Outcome: Low usage		
	1a	1b	2a	2b	2c
Perceived ease of use	●	●			○
Perceived usefulness	●	●		○	●
Peer influence	○	●	●		○
Seniority	●	○	○	○	●
Age	○	○	●	○	○
Gender	○	●	○	●	●
Consistency	0.61	0.61	0.98	0.89	0.81
Raw coverage	0.07	0.04	0.02	0.03	0.06
Unique coverage	0.07	0.04	0.02	0.03	0.06
Solution coverage	0.11		0.11		
Solution consistency	0.61		0.86		

Note: Black circles indicate the presence of a condition and empty circles indicate the absence of a condition. Frequency cut-off: 1. MMA high usage intensity consistency cut-off: 0.61. MMA low usage intensity consistency cut-off: 0.80.

Table 5
Coefficients for doctors' high MMA usage intensity using logistic regression.

Variable	B	S.E.	e^B
Perceived usefulness	1.05***	0.28	2.85
Perceived ease of use	0.55*	0.26	1.73
Constant[a]	− 6.88***	1.362	0.001

Note: e^B = exponential B. Variables not present in the final model are omitted.
[a] Hosmer and Lemeshow test, Chi Square: 7.09, df = 7, sig: 0.420.
*** Significant at $p < 0.001$.
* Significant at $p < 0.05$, $n = 199$, Nagellkerke $R^2 = 0.171$.

random subsamples (Woodside, Schpektor, & Xia, 2013; Wu et al., 2014). Consistency and raw coverage are highly similar between the two subsamples and between the subsamples and the configurations leading to low MMA usage intensity in Table 3.

Tables 4 and 5 present the findings of LR analysis, which add to the fsQCA results presented above. Table 4 shows that MMA usage intensity correlates positively with perceived ease of use and perceived usefulness. However, no significant correlation is observed between MMA usage intensity and peer influence, seniority, age, or gender.

The forward stepwise regression method is used to select predictor variables, starting with a model that contains only the constant, then adding new variables based on entry and removal criteria. As presented in Table 5, increases in perceived usefulness and perceived ease of use are associated with an increase in MMA usage intensity. The model suggests that an increase in perceived usefulness is about 2.9 times more likely to intensify MMA usage. An increase in perceived ease of use is 1.73 times more likely to promote MMA usage intensity. However, LR coefficients should be interpreted with caution, as configuration membership is symmetrically associated with MMA usage intensity. For example, the positive effect of high perceived ease of use on high MMA usage intensity does not necessarily imply an equal negative effect of low perceived ease of use on low MMA usage intensity.

5. Discussion and conclusion

This study analyses six conditions (perceived ease of use, perceived usefulness, peer influence, seniority, age, and gender) that affect MMA usage intensity. Given the limited empirical evidence about complex configurations of enablers of MMA usage intensity, the study uses both LR and fsQCA analyses to gain a nuanced understanding of the relationship between the drivers and the outcome. The LR results suggest that high MMA usage intensity depends on perceived usefulness and perceived ease of use, which is consistent with previous findings (e.g., Kim & Chang, 2007; Tung et al., 2008). Mobile intuitive apps that effectively support the clinical practice attract an increasing number of doctors and promote the use of medical apps. The fsQCA analysis brought new layers of analysis to light – namely, the advantages of dealing with the outcome and the negation of the outcome, as defended by Schneider and Wagemann (2010) and Woodside (2014). The fsQCA analysis shows that low MMA usage intensity is associated with low perceived ease of use, high perceived usefulness, low peer influence, high seniority, and younger female doctors. The fact that female doctors are associated with low MMA usage intensity is not consistent with Sandholzer et al.'s (2015) results. One possible explanation is that female doctors may readily install apps but subsequently use them less often than men. LR and fsQCA analyses agree that perceived ease of use and perceived usefulness contribute to MMA usage intensity. However, fsQCA adds to these results. Peer influence, seniority, age, and gender can all have positive and negative effects on MMA usage intensity. These results suggest that no configuration of enablers is sufficient to explain low MMA usage intensity.

MMAs are increasingly important for the health industry to connect more with doctors. Studying how enablers of MMAs relate to higher levels of usage intensity allows the health industry to better understand how to link and improve communication with the medical profession. Ultimately, there are many beneficiaries from an improvement in MMAs: doctors, medical students, patients, health authorities, suppliers, and researchers, to name but a few.

This paper shows the all-important need to use more than one method to produce a profoundly more meaningful analysis for academics and practitioners alike. The use of the LR method alone would not have enabled us to uncover multiple combinations of conditions, which can lead to the same outcome. To the best of our knowledge, this study is one of the first to explore MMA usage intensity drivers through the parallel application of more than one research method. Nevertheless, some limitations of the study must be noted. First, the results do not demonstrate the evolution of usage intensity over multiple time periods. Second, the participants are all volunteers from the medical profession, and therefore the self-reported measures may not be representative of the total population. Other drivers of MMA usage may also explain intensity, such as compatibility or relative advantage. We suggest that this improvement be brought about by focusing on the low usage factors, because, statistically, this is where there is the most

Table 4
Descriptive measures and correlations.

		α	Mean	SD	1	2	3	4	5	6
1	Perceived Ease of Use	0.795	3.67	0.65	–					
2	Perceived Usefulness	0.865	4.02	0.63	0.248**	–				
3	Peer Influence	–	2.69	0.92	0.112	0.050	–			
4	Usage Intensity	–	–	–	0.226**	0.321**	0.124	–		
5	Seniority	–	–	–	0.046	− 0.020	0.008	0.115	–	
6	Age	–	–	–	− 0.098	0.018	− 0.070	− 0.035	0.109	–
7	Gender	–	–	–	− 0.117	− 0.050	0.204**	− 0.270	0.005	− 0.048

** Significant at $p < 0.01$, $n = 199$.

opportunity for significant change. Future studies could also clarify the results through qualitative research, further exploring the role of perceived ease of use, perceived usefulness, peer influence, seniority, age, and gender in the adoption of MMA.

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