Understanding the Behavioral Determinants of First Responder App Adoption: Integrating UTAUT and Health Belief Model Perspectives

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Abstract

Background: Out-of-hospital cardiac arrests (OHCA) are a leading cause of death worldwide, yet first responder apps can significantly improve outcomes by mobilizing citizens to perform CPR before professional help arrives. Despite their importance, understanding of these apps' societal integration remains limited.

Objective: Given that first responder app use involves elements of both technology adoption and preventive health behavior, it is essential to examine this behavior from multiple theoretical perspectives. Building on the UTAUT and Health Belief Model (HBM), this study therefore developed an integrative framework to explain which behavioral determinants and individual factors drive individual’s willingness to install a first responder app for OHCA.

Methods: We conducted an online cross-sectional survey (N=3660, Mage=49.95, SDage=16.75, 52.2% female) in June 2024 among [country blinded] adults. To test our hypotheses and address our research questions, we developed a Structural Equation Model (SEM) using the Lavaan package in R.

Results: Our results revealed that two UTAUT variables (i.e. facilitating conditions and social influence) and three HBM variables (i.e. perceived susceptibility, perceived barriers and perceived benefits) were associated with willingness to install a first responder app for OHCA. Additionally, most demographic and health factors indirectly related to willingness via behavioral determinants, with age being the sole moderator.

Conclusions: Overall, the results of this study have both theoretical and practical implications. Theoretically, this study finds its relevance in extending the UTAUT and HBM to altruistic mobile health apps and advancing our understanding of technology adoption in health contexts. Practically, the study’s findings could inform real-life health campaigns aimed at enhancing citizen participation in first responder systems.

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Understanding the Behavioral Determinants of First Responder App Adoption: Integrating UTAUT and Health Belief Model Perspectives

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Results: Our results revealed that two UTAUT variables (i.e. facilitating conditions and social influence) and three HBM variables (i.e. perceived susceptibility, perceived barriers and perceived benefits) were associated with willingness to install a first responder app for OHCA. Additionally, most demographic and health factors indirectly related to willingness via behavioral determinants, with age being the sole moderator.

Conclusions: Overall, the results of this study have both theoretical and practical implications. Theoretically, this study finds its relevance in extending the UTAUT and HBM to altruistic mobile health apps and advancing our understanding of technology adoption in health contexts. Practically, the study's findings could inform real-life health campaigns aimed at enhancing citizen participation in first responder systems.

Keywords: mHealth; out-of-hospital cardiac arrest; first responder app; UTAUT; Health Belief Model; health technology adoption; cardiopulmonary resuscitation

Understanding the Behavioral Determinants of First Responder App Adoption: Integrating UTAUT and Health Belief Model Perspectives

Introduction

With the widespread use of mobile phones, the potential of technology to improve health outcomes has significantly increased [1]. Many people, for example, use their mobile devices to install applications for medical and public health practices, better known as mHealth [2]. Most of these apps enable users to monitor their health by for instance tracking their steps or creating personalized diet plans [3,4]. Additionally, besides promoting self-tracking, some mHealth apps can also be used to enhance the health of others and benefit society overall. Examples of such altruistic mHealth apps include contact tracing apps, used during the recent COVID-19 pandemic [5], and first responder apps.

First responder applications alert and mobilize trained citizens to provide first aid in emergency situations, such as experiencing an out-of-hospital cardiac arrest (OHCA) [6]. Suffering an OHCA is a leading cause of death worldwide [7] and in order to tackle this public health problem, early recognition of an OHCA and responding quickly to the situation are crucial. The use of a first responder application could thus be critical in this case as citizens can be alerted to provide cardiopulmonary resuscitation (CPR) before the arrival of professional medical help, thereby ensuring a higher chance of survival [6,8]. However, despite the significant value of these apps, little is still known about their integration within societies for two reasons. First, these apps offer health benefits for others but not directly for users themselves, thereby leaving a gap in our understanding of users' motivations behind adopting these altruistic apps. Second, first responder apps for OHCA differ substantially from other mHealth apps, as they are not designed for frequent use. Once installed, users are only required to engage with the app when they receive a notification requesting assistance for someone suffering a cardiac arrest. As such, given this infrequent usage, it is crucial to understand individuals' willingness to install first responder apps for OHCA in order to promote the adoption of such apps in society.

Therefore, the current study aims to contribute to the literature by defining which behavioral and individual factors play a role in citizens' willingness to install a first responder app for OHCA. Given that first responder app use involves elements of both technology adoption and preventive health behavior, it is essential to examine this behavior from multiple theoretical perspectives, including the Unified Theory of Acceptance and Use of Technology (UTAUT) [9] and the Health Belief Model (HBM) [10]. Based on these theories, we will develop an integrated framework to explain the behavioral determinants that drive individuals' willingness to install altruistic mobile health apps, i.e. first responder apps for OHCA. Additionally, demographic and health variables will be examined to provide a comprehensive understanding of factors driving adoption willingness.

Technology Perspective: UTAUT

To address the technology-related aspect of first responder app adoption, the study builds on the UTAUT model [9], a commonly used theoretical model for predicting the adoption of new technologies. The model consists of four key behavioral determinants of technology adoption: performance expectancy (i.e. perceived effectiveness of the technology), effort expectancy (i.e. the degree of ease associated with using the technology), social influence (i.e. descriptive and injunctive norms) and facilitating conditions (i.e. resources available that make it easier to adopt the new technology, such as internet access and owning a smartphone).

Given that this model integrates elements from various models and theories related to technology acceptance, it has been used frequently in the past to explain the adoption of apps that require frequent and consistent interaction, such as mobile banking apps [11], health monitoring apps [12,13], or travel apps [14]. Moreover, besides these frequently used apps, UTAUT has also been successful in explaining the adoption of contact tracing apps (CTAs) [5,15–18]. Studies, for example, found that users were more inclined to install CTAs when they perceived the app as effective [5,17,18], and easy to use [18]. Additionally, social influence [16] and facilitating conditions, like smartphone ownership [19], were crucial predictors of CTA adoption. The study by Walrave et al.[19], for example, showed that not owning a smartphone was one of the main reasons for not using a CTA.

These studies on CTAs, in turn, offer a relevant comparison for our study as these apps, similar to first responder apps for OHCA, benefit public health and involve passive use (i.e. only interacting when receiving a notification). Based on their insights, it is thus reasonable to assume that the factors outlined in the UTAUT model could also serve as effective predictors for the willingness[a] to install a first responder app for OHCA, apps characterized by their altruistic nature, focus on immediate action and infrequent use. Building on the UTAUT model, this study therefore extends the literature by forming the following hypotheses:

H1: Performance expectancy is positively associated with the willingness to install a first responder app for OHCA.

H2: Effort expectancy is negatively associated with the willingness to install a first responder app for OHCA.

H3: Facilitating conditions are positively associated with the willingness to install a first responder app for OHCA.

H4: Social influence is positively associated with the willingness to install a first responder app for OHCA.

Health Perspective: Health Belief Model

When installing a first responder app, individuals are not merely installing new software but are committing to potentially performing life-saving actions, i.e. providing CPR to someone suffering a cardiac arrest. Relying solely on a technological perspective, such as the UTAUT model, would therefore be insufficient to fully understand individual's willingness to install a first responder app for OHCA. Logically, this decision requires consideration of the health-related implications and responsibilities associated with the app's use. Therefore, in addition to examining first responder app

[a] Based on the Prototype Willingness Model, we will focus on willingness to install a first responder app in this study. The decision is based on the fact that such an app is not yet developed in [country blinded], thus making it challenging to examine behavioral intentions or actual usage at this stage.

adoption through the lens of technology acceptance, it is essential to apply a health behavior change model to better understand the factors influencing the adoption of a first responder app for OHCA.

To do so, we will integrate the Health Belief Model (HBM) [20], which is a widely recognized framework for understanding health-related behavior. The HBM suggests that individuals' decisions to take health actions are influenced by five different factors: perceived susceptibility (i.e. belief in the risk of experiencing a health problem), perceived severity (i.e. belief in the seriousness of the health problem), perceived benefits (i.e. factors that facilitate the health behavior), and perceived barriers (i.e. factors that hinder the health behavior). In this context, a perceived benefit might be personal relevance [21], while a potential barrier could include privacy concerns [22]. Self-efficacy (i.e. confidence in performing the health behavior) was later added as the fifth variable [20].

The model is often employed to explain health behaviors aimed at protecting or improving one's own health, such as condom use [23], or using mobile apps for managing chronic diseases [24]. However, limited research has explored the effectiveness of the HBM in predicting altruistic health behavior like providing CPR. Unlike self-beneficial behaviors, installing a first responder app, and thus committing oneself to potentially performing CPR, is a health behavior that only benefits another individual (i.e. person suffering a cardiac arrest). Several studies have examined the application of the HBM in the context of contact tracing app adoption, which can also be considered an altruistic health behavior as its primary goal is to minimize the spread of COVID-19. These studies indicate that self-efficacy, perceived barriers and perceived benefits are the most significant predictors of adoption [18,25]. For instance, participants were more inclined to install the app when they felt confident in using it, recognized its benefits, and perceived fewer barriers to its adoption. While perceived severity and susceptibility have not consistently predicted adoption in studies on CTAs, they have shown positive associations with preventive health behaviors, such as mask-wearing [26]

Despite these insights related to CTAs, research on first responder apps and the determinants outlined in the HBM is limited. Still, building on findings from previous studies, the HBM likely also applies to the adoption of first responder apps for OHCA. For instance, as these apps can prevent severe outcomes, such as death or brain injury [27], individuals who perceive OHCA as a severe health risk may be more willing to install the app to be able to prevent such serious consequences. Also, perceived susceptibility may influence willingness by heightening awareness of the app's necessity in addressing a widespread health risk in society. Additionally, because of the similar altruistic and preventive nature of CTAs, we can expect that self-efficacy and perceived benefits may positively influence the willingness to install a first responder app, while perceived barriers may negatively influence it.

Building on these insights, this study therefore aims to provide an extensive overview of how the variables of the HBM can explain the willingness to install a first responder app for OHCA. Based on current literature on mHealth apps and preventive health behavior, we propose the following hypotheses:

H5: Self-efficacy is positively associated with the willingness to install a first responder app for OHCA.

H6: Perceived susceptibility is positively associated with the willingness to install a first responder app for OHCA.

H7: Perceived severity is positively associated with the willingness to install a first responder app for OHCA.

H8: Perceived barriers are negatively associated with the willingness to install a first responder app for OHCA.

H9: Perceived benefits are positively associated with the willingness to install a first responder app for OHCA.

Influential Factors

Apart from the previously mentioned direct determinants of first responder app adoption, the HBM also identified a number of indirect factors affecting health behavior, including demographic factors and prior contact with the health problem [10]. Other health behavior change models like Theory of Planned Behavior [28] and Social Cognitive Theory [29] also emphasize the importance of demographic (e.g. age, gender and socio-economic status) and social context variables in shaping individual's beliefs, attitudes and social norms. Moreover, these theoretical propositions have also been confirmed in empirical research as, for example, older people tend to perceive health issues, such as COVID-19, as more severe [30].

Along with demographic variables, practicing a medical profession may also play a significant role in installing a first responder app for OHCA. Individuals working in the medical sector could, for example, perceive greater benefits from using such an app, as it can improve patient outcomes through bystander CPR [6,8]. Consequently, their perceived barriers to installing the app and expectations regarding its effectiveness may also be shaped by their professional experience and familiarity with emergency medical care.

In addition, as installing a first responder app for OHCA is a health-related behavior, the general health status of an individual and other relevant health variables should also be taken into account. First, given that CPR training significantly enhances the willingness to provide CPR [31,32], we could assume that trained individuals will be more likely to install a first responder app for OHCA, potentially via various behavioral determinants such as increased self-efficacy and perceived benefits. Second, the HBM highlights the relevance of prior contact with a health problem as a factor that can increase perceived susceptibility and severity, thereby influencing behavior [10]. In this study, having a cardiovascular disease and, therefore, an increased change of suffering a cardiac arrest, can be a relevant factor. Finally, indirect contact with health issues, such as having a family member or close acquaintance with a cardiovascular disease, could also affect individuals' perceptions and decisions to adopt health-related behaviors like installing a first responder app for OHCA.

Since relationships between these influential factors (i.e. demographic and health variables) and behavioral determinants of first responder app adoption have not been tested before, we pose the following research question:

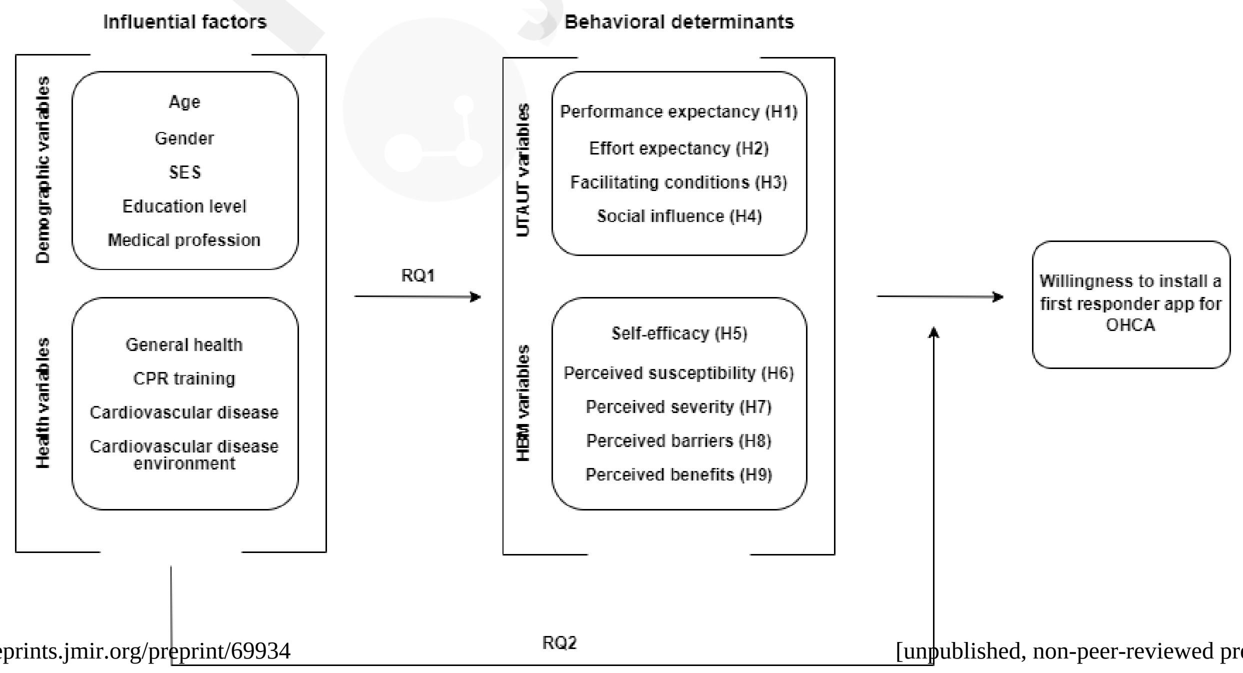
RQ1: Do demographic and health variables influence the behavioral determinants of willingness to install a first responder app for OHCA (performance expectancy, effort expectancy, social influence, facilitating conditions, self-efficacy, perceived severity, perceived susceptibility, perceived barriers and perceived benefits)?

In addition to examining the variables mentioned above as predictors, it may be valuable to explore their potential moderating role. In the UTAUT model, gender and age already moderate the relationships between the key determinants and technology adoption [9,33]. For example, the relationship between performance expectancy and the intention to adopt a technology was stronger for men and young people, but the opposite was found for the other determinants [9,34]. Additionally, empirical research indicates that an individual's education level moderates relationships between certain UTAUT variables (i.e. performance expectancy and social influence) and individuals' willingness to adopt new software [35]. This suggests that similar effects could be found for other demographic and health-related variables in the context of first responder OHCA apps. As there are again a limited amount of studies that investigated these moderations, we will examine the following research question:

RQ2: Do demographic and health variables moderate the relationships between the behavioral determinants (performance expectancy, effort expectancy, social influence, facilitating conditions, self-efficacy, perceived severity, perceived susceptibility, perceived barriers and perceived benefits) and individuals' willingness to install a first responder app for OHCA?

Overall, to fully understand the willingness to install a first responder app for OHCA, this study will evaluate a self-developed integrative framework that incorporates determinants from the UTAUT and Health Belief Model, along with additional influential factors that are particularly relevant to this context (Figure 1).

Figure 1. Conceptual framework of understanding and predicting willingness to install a first responder app for OHCA.



Method

Procedure and Sample

To test our hypotheses and address our research questions, we conducted a cross-sectional survey in June 2024 among a representative sample of [country blinded] adults. Participants were recruited out of a representative panel by a research agency, which was also responsible for reimbursing participants via a points-awarding system. Respondents were asked to fill in an online Qualtrics questionnaire in both Dutch and French, given the bilingual nature of the country. At the beginning of the survey, they were informed about the study's objectives, procedures and the confidentiality of their data, and consent had to be given. Given the online procedure, the involved researchers were available via email to answer questions and solve practical and logistic issues. The study received ethical approval from the university's ethics committee (approval number blinded).

Out of the initial 3,908 respondents, only those who completed more than the socio-demographic section were included. After removing 92 ineligible cases (underage, duplicate responses, or lack of consent), the final sample was 3,660 participants, with a mean age of 49.95 years (*SD* = 16.75); 52.2% were women. The sample included 2,205 Dutch-speaking and 1,455 French-speaking respondents. Education levels varied, with 1.6% having no formal education, 3.9% primary, 36% secondary, 28.9% bachelor's, 26.5% master's, and 3% PhD. Socio-economic status (SES) was assessed using the MacArthur SSS scale [36]: 4% low SES (scores 1-3), 70.3% medium SES (scores 4-7), and 25.5% high SES (scores 8-10). Health-related data showed 10.1% worked as medical professionals, 58.8% had CPR training, 15.4% had a cardiovascular disease, and 30.4% knew someone with a cardiovascular disease.

Measures

Demographic Variables

Respondents' gender (1 = *Male*, 2 = *Female*, 3 = *Other*), year of birth, education level

(1 = *No degree*, 2 = *Primary school degree*, 3 = *Secondary school degree*, 4 = *Bachelor's degree*, 5 = *Master's degree*, 6 = *PhD*) and subjective SES were questioned [36]. Respondents were also asked if they practice a medical profession (1 = *Yes*, 0 = *No*).

Health Variables

We asked respondents whether they had ever followed a CPR training (1 = *Yes*, 0 = *No*), and whether they (1 = *Yes*, 0 = *No*) or people in their surroundings (1 = *Yes*, 0 = *No*) suffer from a cardiovascular disease. Additionally, general health was measured with an adapted version of the Linear Analogue Scale [37]. Respondents had to indicate their general health condition on a scale from 1 (worst) to 100 (best). On average, participants scored 71.11 (*SD* = 18.05), suggesting that the overall health of our sample was good.

Willingness to Install a First Responder App for OHCA

To measure participants' willingness to install a first responder app for OHCA, participants first received an explanation of what is meant with a first responder app. They were told that a first responder app for OHCA is a mobile application that alerts and mobilizes volunteer citizens to provide first aid to someone suffering a cardiac arrest. Additionally, we explained the different features of the app (e.g. location-based technology), the goal of the app and that such an app is currently being set up in their country of residence [blinded for review]. Next we asked respondents if they ever heard of a first responder app (13.5% heard of a first responder app) and to indicate on a 5-point Likert scale (1 = *Totally disagree* to 5 = *Totally agree*) to what extent the following statement applied to them: "If a first responder app for OHCA is available in [country blinded], I am willing to install it". The mean score of 3.64 (*SD* = 1.03) indicates a moderately high willingness to install the app.

Behavioral Determinants

UTAUT Determinants

Performance Expectancy

Based on the definition given by Venkatesh et al. [9], performance expectancy was measured by a self-developed scale which asked respondents to indicate on a 5-point Likert scale (1 = *Totally disagree* to 5 = *Totally agree*) to what extent the following two statements applied to them: "This first responder app is an effective application for saving individuals suffering a cardiac arrest." and "This first responder app would ensure that fewer people die from a cardiac arrest.". In these statements, *this* refers to the particular first responder app for OHCA in [country blinded] that is being set up. We found a high correlation between the two items (r = .75, P < .001) and merged together in one variable. On average, participants scored 3.90 (SD = .78), indicating a strong positive perception of the app's effectiveness.

Effort Expectancy

This was assessed using a 5-point Likert scale (1 = *Totally disagree* to 5 = *Totally agree*) item adapted from van der Waal et al. [18], asking participants to rate the statement, "I think it will cost me a lot of time and energy to install this first responder app.". The average score was 2.06 (SD = 1.05), indicating that most participants found the app easy to install.

Facilitating Conditions

Facilitating conditions were measured with a 5-point Likert scale (1 = *Totally disagree* to 5 = *Totally agree*) item based on van der Waal et al. [18], asking participants to rate the statement, "I have a smartphone with internet access, allowing me to install this first responder app." The mean score of 4.04 (SD = 1.08) indicates high smartphone ownership and internet access among respondents.

Social Influence

Social influence was surveyed by measuring both injunctive and descriptive norms.

We developed two items based on the definitions of Rimal and Real [38]. Injunctive norms were measured by asking respondents to indicate on a 5-point Likert scale (from 1 = *Totally disagree* to 5 = *Totally agree*) to what extent the following statement applied to them: "Most people in my environment would have a positive attitude towards this first responder app.". Descriptive norms were measured by: "Most people in my environment would install this first responder app, if this app would be available in [country blinded].", and was evaluated on a 5-point Likert scale. Both norms were combined in social influences, as they were correlated (r = .65, P < .001). With an average score of 3.28 (SD = .78), the results indicate that social influences were moderately strong, meaning that the participants believed a fair number of people in their environment would install the first responder app and have a positive attitude towards it.

Health Belief Model Determinants

Self-Efficacy

A self-developed scale based on the definition of Bandura [29] asked respondents to indicate on a 5-point Likert scale (from 1 = *Totally disagree* to 5 = *Totally agree*) to what extent the following two statements applied to them: "It seems difficult to install this first responder app." and "I would be able to install this first responder app if I wanted to.". The first item was recoded for analysis and then merged with the second item into one construct, as there was a significant correlation between the two items (r = .45, P < .001). Participants scored high on self-efficacy (M = 3.92, SD = .87), suggesting that they feel confident in their ability to successfully install a first responder app.

Perceived Susceptibility of an OHCA

Perceived susceptibility was assessed on both personal and societal levels using self-developed items based on El-Toukhy [39]. Respondents rated their own risk (personal perceived susceptibility) and the average person’s risk (societal perceived susceptibility) of suffering a cardiac arrest on a 5-point Likert scale (1 = *Very low* to 5 = *Very high*). Personal and societal susceptibility were correlated (r = .56, P < .001) and combined into one measure with a mean of 2.90 (*SD* = .64), indicating a moderate perceived susceptibility of an OHCA.

Perceived Severity of an OHCA

To measure respondents' perceived severity of an OHCA on a personal an societal level, a self-developed scale adapted from El-Toukhy [39] asked them to indicate on a 5-point Likert scale (from 1 = *Totally disagree* to 5 = *Totally agree*) to what extent the following two statements applied to them: "I believe that if I suffer a cardiac arrest, it could have serious consequences for me." and "I believe that if someone suffers a cardiac arrest, it can have serious consequences for that person.". The items, personal and societal perceived severity respectively, correlated with each other (r = .71, P < .001) and a mean score was calculated by averaging the two items. On average, participants perceived a OHCA as very severe (*M* = 4.45, *SD* = .74).

Perceived Barriers

Based on technology and health behavior literature [19,21,40], we created 14 different items that reflected various barriers that respondents could experience while installing a first responder application (see Appendix). Examples of these barriers included phone-related issues, digital difficulties, privacy violations and credibility of the app. Respondents had to indicate on a 5-point Likert scale (from 1 = *Totally disagree* to 5 = *Totally agree*) to what extent the statements applied to them (e.g. "I would not install this first responder app because I'm afraid my privacy will not be guaranteed."). A manifest variable was created by summing the scores of all 14 items (Min=14 – Max=70). Consequently, a low score on this variable indicates that a participant experiences few barriers, while a high score suggests that a participant encounters many barriers when it comes to installing a first responder app for OHCA. On average, participants scored 29.75 (*SD* = 10.70), indicating that they generally did not feel substantially hindered in their ability to install the app.

Perceived Benefits

For perceived benefits, we developed five items which reflected various benefits respondents could perceive about installing a first responder application for OHCA (see Appendix), based on previous studies on altruistic health apps and providing CPR [21,31,41]. We measured benefits like personal relevance and altruistic satisfaction. Respondents had to indicate on a 5-point Likert scale (from 1 = *Totally disagree* to 5 = *Totally agree*) to what extent the statements applied to them (e.g. “I would install this first responder app because it is my duty to help people.”). A manifest variable was formed by adding the scores from all 5 items, resulting in a possible range of 5 to 25. A lower score on this variable reflects fewer perceived benefits, while a higher score indicates more benefits related to installing a first responder app. The average participant score was 18.17 (SD = 3.47), suggesting that most respondents saw the app as advantageous.

Analyses

After data cleaning, descriptive statistics and zero-order correlations were calculated (see Table 1). Then, we developed a Structural Equation Model (SEM) using the Lavaan package in R to test the hypotheses and address the research questions.

All variables with two items were entered as latent variables, while single-item variables were entered as manifest variables. Subsequently, we specified the regression paths, which were drawn between the behavioral determinants (i.e., performance expectancy (H1), effort expectancy (H2), facilitating conditions (H3), social influence (H4), self-efficacy (H5), perceived susceptibility (H6), perceived severity (H7), perceived barriers (H8), and perceived benefits (H9); independent variables) and the willingness to install a first responder app for OHCA (i.e., dependent variable) to answer our nine hypotheses. Additionally, to examine RQ1, paths were specified between the behavioral determinants as dependent variables and the influential factors (i.e. demographics and health variables) as independent variables.

To explore RQ2 and examine the moderating role of the influential factors on the relationships between the behavioral determinants and the willingness to install a first responder app for OHCA, multiple group analyses were conducted. We created groups based on the median for age, socio-economic status (SES), general health, and education. For age, we compared younger and older participants; for SES, we compared low and high SES groups; for health, we compared poor and good health; and for education, we compared lower and higher educational attainment. Gender was recoded as a dichotomous variable, as the group of 11 participants who selected "other" was too small for meaningful analysis; these responses were therefore treated as missing values. The variables for medical profession, CPR training, cardiovascular disease, and cardiovascular disease in one's environment were also dichotomous, meaning that participants were already divided into two distinct groups for each variable. The constrained model (i.e., the model in which the paths of the behavioral determinants to willingness were specified to be the same across groups) was then compared with an unconstrained model (i.e., the model in which the paths of the behavioral determinants to willingness were allowed to differ across groups), and a chi-square difference test was conducted to assess whether the model fit differed significantly between the groups.

The following indices were used to assess the model fit: Chi-square/ degrees of freedom (χ^2/df), Comparative Fit Index (CFI), Tucker-Lewis Index (TLI), Root Mean Square Error of Approximation (RMSEA), 90% confidence interval for RMSEA, and Standardized Root Mean Square Residual (SRMR). The overall hypothesized model indicated an acceptable fit ($\chi 2 = 1230.791$, $df = 95$, $p < .001$, RMSEA =.060, 90% CI [.057, .063], CFI = .950, TLI = .874, SRMR = .030). Although the χ^2 (df) statistic and corresponding p-value are reported, they were not used as the primary criterion for model acceptance or rejection, given that reliance on χ^2 (df) alone can be overly restrictive in many research contexts.

Hypotheses and the analysis plan were preregistered on the Open Science Framework (OSF).

Results

Descriptive Analyses

Table 1 shows the descriptive statistics and zero-correlations between the different variables within the model.

Table 1. Statistics and zero-order correlations.

	SD	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19
-	-	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
96	16.7[illegible]	.067[b]	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
84	1.0[illegible]	-.046[b]	-.087[b]	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
-	-	-.104[b]	-.100[b]	.051[b]	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-	-
57	1.47	.003	.064[b]	.404[b]	.053[b]	1	-	-	-	-	-	-	-	-	-	-	-	-	-	-
11	18.05	.030	-.126[b]	.205[b]	.036[c]	[illegible]05[b]	1	-	-	-	-	-	-	-	-	-	-	-	-	-
-	-	.065[b]	.251[b]	-.062[b]	-.005	-.040[c]	-.234[b]	1	-	-	-	-	-	-	-	-	-	-	-	-
-	-	-.054[b]	-.018	-.014	.082[b]	[illegible]21	-.093[b]	.187[b]	1	-	-	-	-	-	-	-	-	-	-	-
-	-	-.014	-.184[b]	.036[c]	.160[b]	[illegible]0[b]	.077[b]	-.041[c]	.051[b]	1	-	-	-	-	-	-	-	-	-	-
.9	.78	-.001	.073[b]	-.002	-.024	.040[c]	.057[b]	.000	-.006	.039[c]	1	-	-	-	-	-	-	-	-	-
06	1.05	-.028	.224[b]	-.140[b]	.068[b]	-.096[b]	-.124[b]	.111[b]	.052[b]	-.124[b]	-.220[b]	1	-	-	-	-	-	-	-	-
28	.78	-.002	-.051[b]	.007	.037[c]	.053[b]	.054[b]	-.014	.000	-.029	.407[b]	-.087[b]	1	-	-	-	-	-	-	-
04	1.08	-.001	-.207[b]	.132[b]	-.007	.118[b]	.128[b]	-.075[b]	.007	.107[b]	.224[b]	-.377[b]	.136[b]	1	-	-	-	-	-	-
02	.53	.014	-.310[b]	.156[b]	-.042[c]	.099[b]	.141[b]	-.119[b]	-.024	.134[b]	.286[b]	-.660[b]	.134[b]	.530	1	-	-	-	-	-
90	.64	.017	.421[b]	-.210[b]	.002	-.137[b]	-.259[b]	.229[b]	.087[b]	-.095[b]	.048[b]	.214[b]	.006	.175[b]	-.233[b]	1	-	-	-	-
45	.74	.004	.016	.179[b]	-.074[b]	.106[b]	.087[b]	.011	.009	.095[b]	.188[b]	-.249[b]	-.011	.230[b]	.258[b]	-.061[b]	1	-	-	-
75	10.70	-.053[b]	.019	-.114[b]	.061[b]	-.127[b]	-.151[b]	.069[b]	.048[b]	-.102[b]	-.434[b]	.531[b]	-.299[b]	-.398[b]	-.528[b]	.144[b]	-.208[b]	1	-	-
18	3.4[illegible]	.013	-.044[c]	-.007	.133[b]	.037[c]	.084[b]	-.009	-084[b]	.273[b]	.485[b]	-.164[b]	.400[b]	.232[b]	.251[b]	.063[b]	.130[b]	-.444[b]	1	-
64	1.0[illegible]	.025	-.073[c]	.004	.053[b]	.034	.097[b]	-.027	.020	.113[b]	.391[b]	-.221[b]	.397[b]	.257[b]	.280[b]	.015	.085[b]	-.494[b]	.585[b]	1

[a] $p < .001$
[b] $p < .01$
[c] $p < .05$
[d] Gender is coded: woman = 1, man = 2, other = 3.
[e] Medical prof., Cv. Disease, CPR training and Cv. Disease environ. are coded: yes = 1 and no = 0.

		1. Gender[d]	2. Age	3. Education level	4. Medical profession[e]	5. SES	6. General health	7. Cardiovascular disease[e]	8. Cardiovascular disease environment[e]	9. CPR training[e]	10. Performance expectancy	11. Effort expectancy	12. Social influences	13.Facilitating conditions	14. Self-efficacy	15. Perceived susceptibility	16. Perceived severity	17. Perceived barriers	18. Perceived benefits	19. Intention to install a first responder app

SEM

Relations Between Behavioral Determinants and Willingness to Install a First Responder App for OHCA

Parameter estimates can be found in Table 2. First, regarding H1 on the association between performance expectancy and willingness to install a first responder app for OHCA, we found no significant relationship between the two variables. H2 was also rejected as we did not find a significant association between effort expectancy and willingness to install a first responder app for OHCA. For H3, we found that more facilitating conditions were related to a higher willingness to install a first responder app for OHCA, which consequently confirms the hypothesis. In addition, social influence positively predicted willingness to install a first responder app for OHCA, thus confirming H4. However, there were no significant associations between willingness to install a first responder app for OHCA, self-efficacy (H5) and perceived severity (H7), thus refuting H5 and H7. Perceived susceptibility on the other hand was positively related with the willingness to install a first responder app for OHCA, confirming H6. Lastly, the strongest associations with willingness to install a first responder app for OHCA occurred for perceived barriers (H8) and perceived benefits (H9), confirming H8 and H9.

Relations Between the Influential Factors and the Behavioral Determinants

To answer RQ1, we examined how demographic and health variables related to the behavioral determinants of willingness to install a first responder app for OHCA (see Table 2 for all parameter estimates).

Demographic Variables

The results showed that practicing a medical profession was positively related to effort expectancy, perceived susceptibility, perceived barriers and benefits, but negatively with facilitating conditions, self-efficacy and perceived severity (see Table 2). Age was positively associated with performance expectancy, effort expectancy, and perceived susceptibility, but negatively with facilitating conditions, social influences and self-efficacy. Furthermore, education level correlated with six out of the nine behavioral determinants: negatively with effort expectancy, perceived susceptibility and perceived barriers, and positively with facilitating conditions, self-efficacy and perceived severity. Gender was only positively related to self-efficacy and negatively related to perceived barriers. This means that men had higher levels of self-efficacy and women perceived more barriers to install a first responder app for OHCA. Finally, we found positive relationships between socio-economic status and facilitating conditions and social influences, whereas socio-economic status was negatively correlated with perceived susceptibility (see Table 2).

Table 2. Parameter estimates SEM.

Dependent variable	Predictor	Estimate	Std. Err	Std. Est	P-value	R^2
Intention FRA						.447
	Performance exp.	.036	.031	.026	.240	
	Effort expectancy	-.044	.049	-.045	.360	
	Facilitating cond.	.062[b]	.021	.065[b]	.003	
	Social influences	.228[a]	.029	.157[a]	.000	
	Self-efficacy	-.118	.102	-.097	.243	
	Perceived suscept.	.126[b]	.042	.061[b]	.003	
	Perceived sever.	-.033	.024	-.023	.171	
	Perceived barriers	-.028[a]	.003	-.292[a]	.000	
	Perceived benefits	.111[a]	.005	.375[a]	.000	
	Age	-.006[a]	.001	-.090[a]	.000	
	Gender[c]	.022	.027	.011	.409	
	SES	-.017	.011	-.024	.118	
	Education level	-.013	.015	-.012	.420	
	Medical profession[d]	.055	.047	.016	.241	
	General health	.002	.001	.028	.066	
	Cv. disease[d]	.029	.040	.010	.475	
	CPR training[d]	-.045	.030	-.021	.135	
	Cv. disease environ.[d]	.000	.030	.000	.989	
Performance exp.						.015
	Age	.004[a]	.001	.093[a]	.000	
	Gender	-.028	.028	-.019	.318	
	SES	.007	.011	.014	.516	
	Education level	-.013	.015	-.018	.389	
	Medical profession	-.079	.047	-.032	.093	
	General health	.003[b]	.001	.067[b]	.002	

	Cv. disease	-.013	.041	-.006	.751	
	CPR training	.087[b]	.029	.058[b]	.003	
	Cv. disease environ.	.004	.031	.002	.905	
Effort expectancy						.095
	Age	.013[a]	.001	.203[a]	.000	
	Gender	-.082	.035	-.040	.018	
	SES	-.034	.014	-.048	.014	
	Education level	-.099[a]	.019	-.095[a]	.000	
	Medical profession	.366[a]	.059	.106[a]	.000	
	General health	-.002	.001	-.043	.023	
	Cv. disease	.098	.052	.034	.057	
	CPR training	-.211[a]	.036	-.099[a]	.000	
	Cv. disease environ.	.094	.039	.041	.016	
Facilitating cond.						.073
	Age	-.012[a]	.001	-.190[a]	.000	
	Gender	.026	.036	.012	.480	
	SES	.056[a]	.015	.076[a]	.000	
	Education level	.082[a]	.020	.076[a]	.000	
	Medical profession	-.167[b]	.062	-.047[b]	.007	
	General health	.003[b]	.001	.053[b]	.005	
	Cv. disease	-.018	.054	-.006	.733	
	CPR training	.154[a]	.038	.070[a]	.000	
	Cv. disease environ.	.025	.041	.011	.537	
Social influences						.015
	Age	-.003[a]	.001	-.076[a]	.000	
	Gender	.007	.027	.005	.802	
	SES	.034[b]	.011	.070[b]	.002	
	Education level	-.015	.015	-.022	.305	
	Medical profession	.078	.047	.033	.092	
	General health	.002	.001	.040	.070	
	Cv. disease	.013	.041	.007	.755	
	CPR training	-.072	.029	-.050	.012	
	Cv. disease environ.	.000	.031	.000	.988	
Self-efficacy						.191
	Age	-.017[a]	.001	-.335[a]	.000	
	Gender	.085[b]	.032	.051[b]	.009	
	SES	.028	.013	.049	.032	
	Education level	.110[a]	.018	.131[a]	.000	
	Medical profession	-.358[a]	.055	-.129[a]	.000	
	General health	.003[b]	.001	.058[b]	.009	
	Cv. disease	-.071	.049	-.031	.141	
	CPR training	.180[a]	.034	.105[a]	.000	
	Cv. disease environ.	-.053	.036	-.029	.149	
Perceived suscept.						.428
	Age	.018[a]	.001	.594[a]	.000	
	Gender	.018	.014	.018	.221	
	SES	-.015[b]	.006	-.045[b]	.008	
	Education level	-.057[a]	.008	-.115[a]	.000	

	Medical profession	.123[a]	.025	.075[a]	.000	
	General health	-.003[a]	.000	-.094[a]	.000	
	Cv. disease	.038	.022	.027	.080	
	CPR training	-.031	.015	-.030	.044	
	Cv. disease environ.	.056[b]	.016	.051[b]	.001	
Perceived sever.						.068
	Age	.002	.001	.045	.024	
	Gender	-.013	.026	-.009	.614	
	SES	.007	.010	.014	.515	
	Education level	.135[a]	.014	.195[a]	.000	
	Medical profession	-.248[a]	.044	-.108[a]	.000	
	General health	.001	.001	.038	.069	
	Cv. disease	.052	.038	.027	.172	
	CPR training	.179[a]	.027	.126[a]	.000	
	Cv. disease environ.	.029	.029	.019	.307	
Perceived barriers						.053
	Age	-.008	.012	-.012	.492	
	Gender	-1.018[b]	.360	-.049[b]	.005	
	SES	-.377	.146	-.052	.010	
	Education level	-.726[a]	.199	-.068[a]	.000	
	Medical profession	2.882[a]	.613	.082[a]	.000	
	General health	-.061[a]	.011	-.103[a]	.000	
	Cv. disease	1.159	.540	.039	.032	
	CPR training	-2.325[a]	.380	-.107[a]	.000	
	Cv. disease environ.	.676	.405	.029	.095	
Perceived benefits						.090
	Age	.003	.004	.014	.429	
	Gender	.158	.115	.023	.168	
	SES	.007	.046	.003	.887	
	Education level	-.115	.063	-.033	.069	
	Medical profession	.786[a]	.195	.068[a]	.000	
	General health	.014[a]	.004	.075[a]	.000	
	Cv. disease	-.062	.172	-.007	.717	
	CPR training	1.818[a]	.121	.257[a]	.000	
	Cv. disease environ.	.530[a]	.129	.070[a]	.000	

[a] $p < .001$
[b] $p < .01$
[c] Gender is coded: woman = 1, man = 2, other = 3.
[d] Medical prof., Cv. Disease, CPR training and Cv. Disease environ. are coded: yes = 1 and no = 0.

Health Variables

General health proved to be an important variable as the higher participants rated their health, the higher they scored on performance expectancy, facilitating conditions, self-efficacy and perceived benefits, but the lower they scored on perceived susceptibility and barriers. Moreover, having done a CPR training was also positively related to five behavioral determinants (i.e., performance expectancy, facilitating conditions, self-efficacy, perceived severity and perceived benefits), but negatively with effort expectancy and perceived barriers. Surprisingly, we found no significant associations between any of the behavioral determinants and suffering from a cardiovascular disease oneself. Knowing someone in your close environment who is suffering from a cardiovascular disease, on the other hand, increased perceived susceptibility and perceived benefits of a first responder app for OHCA (see Table 2).

We also explored the indirect relationships between the influential factors and willingness to install the app through the behavioral determinants. Only a limited number of these relationships were significant. Table 3 reports the estimates.

Table 3. Indirect effects.

Indirect relation	Estimate	Std. Err	Std. Est
1. Age → performance exp. → intention	.000	.000	.002
2. Age → effort exp. → intention	-.001	.001	-.009
3. Age → facilitating cond. → intention	-.001[b]	.000	-.012[b]
4. Age → social influences → intention	-.001[b]	.000	-.012[b]
5. Age → self-efficacy → intention	.002	.002	.032
6. Age → perceived suscept. → intention	.002[b]	.001	.036[b]
7. Age → perceived sever. → intention	-.000	.000	-.001
8. Age → perceived barriers → intention	.000	.000	.004
9. Age → perceived benefits → intention	.000	.000	.005
10. Gender → performance exp. → intention	-.001	.001	-.000
11. Gender → effort exp. → intention	.004	.004	.002
12. Gender → facilitating cond. → intention	.002	.002	.001
13. Gender → social influences → intention	.002	.006	.001
14. Gender → self-efficacy → intention	-.010	.009	-.005
15. Gender → perceived suscept. → intention	.002	.002	.001
16. Gender → perceived sever. → intention	.000	.001	.000
17. Gender → perceived barriers → intention	.029[b]	.011	.014[b]
18. Gender → perceived benefits → intention	.018	.013	.009
19. SES → performance exp. → intention	.000	.000	.000
20. SES → effort exp. → intention	.002	.002	.002
21. SES → facilitating cond. → intention	.003	.001	.005
22. SES → social influences → intention	.008[b]	.003	.011
23. SES → self-efficacy → intention	-.003	.003	-.005
24. SES → perceived suscept. → intention	-.002	.001	-.003
25. SES → perceived sever. → intention	-.000	.000	-.000
26. SES → perceived barriers → intention	.011	.004	.015
27. SES → perceived benefits → intention	.001	.005	.001

28. Edu. level → performance exp. → intention	-.000	.001	-.000
29. Edu. level → effort exp. → intention	.004	.005	.004
30. Edu. level → facilitating cond. → intention	.005	.002	.005
31. Edu. level → social influences → intention	-.004	.003	-.003
32. Edu. level → self-efficacy → intention	-.013	.011	-.013
33. Edu. level → perceived suscept. → intention	-.007[b]	.003	-.007[b]
34. Edu. level → perceived sever. → intention	-.004	.003	-.004
35. Edu. level → perceived barriers → intention	.020[b]	.006	.020[b]
36. Edu. level → perceived benefits → intention	-.013	.007	-.012
37. Med. prof. → performance exp. → intention	-.003	.003	-.001
38. Med. prof. → effort exp. → intention	-.016	.018	-.005
39. Med. prof. → facilitating cond. → intention	-.010	.005	-.003
40. Med. prof. → social influences → intention	.018	.011	.005
41. Med. prof. → self-efficacy → intention	.042	.037	.012
42. Med. prof. → perceived suscept. → intention	.016	.006	.005
43. Med. prof. → perceived sever. → intention	.008	.006	.002
44. Med. prof. → perceived barriers → intention	-.081[a]	.019	-.024[a]
45. Med. prof. → perceived benefits → intention	.087[a]	.022	.026[a]
46. Health → performance exp. → intention	.000	.000	.002
47. Health → effort exp. → intention	.000	.000	.002
48. Health → facilitating cond. → intention	.000	.000	.003
49. Health → social influences → intention	.000	.000	.006
50. Health → self-efficacy → intention	-.000	.000	-.006
51. Health → perceived suscept. → intention	-.000[b]	.000	-.006[b]
52. Health → perceived sever. → intention	-.000	.000	-.001
53. Health → perceived barriers → intention	.002[a]	.000	.030[a]
54. Health → perceived benefits → intention	.002	.000	.028[a]
55. Cv. disease → performance exp. → intention	.000	.002	.000
56. Cv. disease → effort exp. → intention	-.004	.005	-.002
57. Cv. disease → facilitating cond. → intention	-.001	.003	.000
58. Cv. disease → social influences → intention	.003	.009	.001
59. Cv. disease → self-efficacy → intention	.008	.009	.003
60. Cv. disease → perceived suscept. → intention	.005	.003	.002
61. Cv. disease → perceived sever. → intention	-.002	.002	-.001
62. Cv. disease → perceived barriers → intention	-.033	.016	-.012
63. Cv. disease → perceived benefits → intention	-.007	.019	-.002
64. CPR training → performance exp. → intention	.003	.003	.001
65. CPR training → effort exp. → intention	.009	.010	.004
66. CPR training → facilitating cond. → intention	.009	.004	.005
67. CPR training → social influences → intention	-.016	.007	-.008
68. CPR training → self-efficacy → intention	-.021	.019	-.010
69. CPR training → perceived suscept. → intention	-.004	.002	-.002
70. CPR training → perceived sever. → intention	-.006	.004	-.003
71. CPR training → perceived barriers → intention	.065[a]	.012	.031[a]
72. CPR training → perceived benefits → intention	.202[a]	.017	.096[a]
73. Cv. dis. env. → performance exp. → intention	.000	.001	.000
74. Cv. dis. env. → effort exp. → intention	-.004	.005	-.002
75. Cv. dis. env. → facilitating cond. → intention	.002	.003	.001
76. Cv. dis. env. → social influences → intention	.000	.007	.000
77. Cv. dis. env. → self-efficacy → intention	.006	.007	.003
78. Cv. dis. env. → perceived suscept. → intention	.007	.003	.003
79. Cv. dis. env. → perceived sever. → intention	-.001	.001	.000
80. Cv. dis. env. → perceived barriers → intention	-.019	.012	-.009
81. Cv. dis. env. → perceived benefits → intention	.059[a]	-.026	.026[a]

[a] $p < .001$
[b] $p < .01$
[c] Gender is coded: woman = 1, man = 2, other = 3.
[d] Medical prof., Cv. Disease, CPR training and Cv. Disease environ. are coded: yes = 1 and no = 0.

The Moderating Role of the Influential Factors

Regarding RQ2, multiple group analyses were performed to examine potential moderating effects of the demographic and health variables (see Table 4a). Age was the only significant moderator in the SEM model with the chi-square difference test indicating a significant difference between the fits of the constrained and unconstrained model ($\Delta\chi 2$ (9) = 23.690, *P* = .005). The post-hoc tests revealed that age differences were only present for two relations within the model (see Table 4b). First, perceived severity was differently related to willingness to install a first responder app for OHCA. For young adults, there was no significant relation (β = .028 , *P* = .489) and for old adults, there was a negative relationship (β = -.072, *P* = .029). Thus, for older people perceiving a cardiac arrest as severe related negatively to willingness to install the app. In addition, the association between perceived benefits and willingness to install a first responder app for OHCA was significantly stronger for older people (β = 0.123, *P* = .000) compared to younger people (β = 0.092, *P* = .000).

Table 4a. Multiple group analyses.

Moderator	Δχ2	ΔDf	P-value
Age	23.690[b]	9	.005
Gender	10.195	9	.335
SES	7.478	9	.588
Education level	6.443	9	.695
Medical profession	11.397	9	.250
Health	8.091	9	.525
Cv. disease	8.704	9	.465
CPR training	9.901	9	.359
Cv. disease environ.	4.890	9	.843

[a] $p < .001$
[b] $p < .01$

Table 4b. Post-hoc chi-square difference tests age.

	Δχ2	P-value	β young	β old
Performance exp. → Intention to install FRA	2.467	.166	-	-
Effort expectancy → Intention to install FRA	.128	.721	-	-
Facilitating cond. → Intention to install FRA	.022	.883	-	-
Social influences → Intention to install FRA	3.013	.083	-	-
Self-efficacy → Intention to install FRA	.885	.346	-	-

Perceived suscept. → Intention to install FRA	.053	.817	-	-
Perceived sever. → Intention to install FRA	3.920[c]	.048	.028	-.072
Perceived barriers → Intention to install FRA	.161	.688	-	-
Perceived benefits → Intention to install FRA	7.820[b]	.005	.092	.123

[a] $p < .001$
[b] $p < .01$
[c] $p < .05$

Discussion

Out-of-hospital cardiac arrests (OHCAs) are one of the leading causes of death worldwide, impacting approximately 350,000 people annually in Europe [7]. With survival rates ranging from 5% to 25% [7], first responder apps for OHCAs offer a vital solution to increase survival rates by mobilizing volunteer citizens to provide CPR in emergency situations. However, despite the emergence of these apps, little is still known about their adoption processes. Building on a comprehensive framework that integrates the UTAUT model, the Health Belief Model, and other contextual variables, this study therefore contributes to the literature by examining which factors influence citizens' willingness to install a first responder app for OHCA.

Main Findings Hypotheses

This study offers partial evidence for the use of UTAUT determinants in understanding the adoption of first responder apps for OHCA, expanding our insights into how the model applies to altruistic mHealth apps. Specifically, only facilitating conditions (H3) and social influence (H4) were positively related to willingness to install a first responder app for OHCA whereas performance and effort expectancy were not. First, aligning with facilitating conditions in studies on CTAs [18,19], people with internet and smartphone access were more willing to install a first responder app for OHCA, which is unsurprising given that these conditions are essential for installing and using a first responder app [19]. In addition, individuals who perceived more positive descriptive and injunctive norms were more willing to install a first responder app for OHCA. This aligns with a systematic review on CTAs showing that social influence is one of the most significant predictors of novel app adoption [16]. Moreover, research shows that social influence is a crucial predictor of the intention to perform bystander CPR [42], which may also help clarify the relationship observed in this study.

Performance (H1) and effort expectancy (H2) were not significantly associated with willingness to install a first responder app for OHCA. While previous studies on CTAs and other health apps have reported mixed results for effort expectancy [5,18,43], performance expectancy has been classified as a strong predictor [13,15,17,18]. These insignificant findings in the current study could be attributed to the fact that the first responder app has not yet been implemented in [country blinded], thus making it hard for individuals to estimate the app's effectiveness (performance expectancy) and ease of use (effort expectancy) based solely on the brief description provided.

Regarding the Health Belief Model (HBM) determinants, we identified three significant relationships (i.e. perceived susceptibility, barriers and benefits) with willingness to install a first responder app for OHCA. First, even though mixed findings occurred for perceived susceptibility in mHealth app literature [18,25,44], this variable was as a significant predictor for the willingness to install a first responder app (H6). This indicates that individuals who perceive themselves to be at a higher risk of experiencing a cardiac arrest are more inclined to adopt the app. Consequently, their personal risk assessment likely influences their perception of the app's importance in society. In addition, perceived barriers (H8) and benefits (H9) were significantly associated with willingness to install a first responder app for OHCA, with barriers negatively and benefits positively relating to willingness. In other words, the more barriers participants perceived, the less likely they were to install the app, while those who saw more benefits were more inclined to install. These findings aligns with previous research on health app adoption and bystander CPR, where barriers such as usability issues or privacy concerns [19,21,22,40], and perceived benefits like personal relevance and altruistic satisfaction [21,31,41], have been shown to be key predictors. Interestingly, perceived barriers and benefits emerged as the strongest predictors, highlighting their critical role in users' willingness to install a first responder app for OHCA.

Finally, there was no significant relationship between self-efficacy (H5) or perceived severity (H7) and willingness to install a first responder app for OHCA. The absence of a link with self-efficacy is surprising as it contradicts studies on contact tracing apps [18,25] and other mobile health technology [45,46], where self-efficacy often emerged as a strong predictor, sometimes even the strongest. One possible explanation could lie in the difference between technology-related and health-related self-efficacy. In health research, self-efficacy often involves confidence in performing complex behaviors, like CPR. As such, for installing a first responder app for OHCA, self-efficacy may not be about installing the app, which can be fairly simple, but rather feeling capable of providing CPR if alerted. This focus on health-related self-efficacy may have been overlooked in this study, possibly explaining the absence of a significant link in the findings. Additionally, mixed results regarding perceived severity have been reported in the literature [18,47], suggesting variability in its influence across different health behaviors. In the context of first responder apps for OHCA, the lack of a significant relationship might be explained by the psychological and physical distance associated with such emergencies. Although citizens recognize that OHCA is a severe, life-threatening condition, they may perceive it as happening outside of their immediate, familiar environment and therefore don't feel a personal sense of responsibility. This feeling of detachment might lessen their willingness to install a first responder app.

Main Findings Research Questions

We formulated two research questions to explore influential factors that may affect the behavioral determinants of willingness to install a first responder app for OHCA and to examine the potential moderating effects of these factors on the relationships between the determinants and willingness. As expected, age proved to be a significant variable for two main reasons. First, it was associated with six of the nine behavioral determinants. Second, it was the only moderating factor in the model. More specifically, there was an age difference in the relation between perceived severity and willingness: no significant link was found for adults under 50, while a negative association was observed for those over 50. Older adults who viewed cardiac arrest as severe were thus less willing to install a first responder app for OHCA. This finding could suggest that older adults, who often have a more skeptical attitude towards technology [48], may perceive a cardiac arrest as a serious issue that requires professional medical intervention, leading to distrust in citizen responders. This skepticism could explain the negative association, but this speculation needs to be tested further. Additionally, there was an age difference in the relationship between perceived benefits and willingness, with a stronger positive relation identified among older adults. The stronger positive relationship may indicate that older people, unlike digital natives, require clearer and more substantial advantages before they are willing to adopt new technologies. This aligns with Rogers' Diffusion of Innovations theory [49], which suggests that individuals assess the relative advantages and disadvantages of an innovation before deciding to adopt it. Moreover, it is in line with the UTAUT model that says that all relationships except for performance expectancy are stronger for older people [9,34].

In accordance with the Health Belief Model [10], also other demographic variables like gender, socio-economic status (SES) and education level were related to several of the behavioral determinants, and in that way indirectly to willingness to install a first responder app for OHCA. For example, younger people and men experienced more self-efficacy, which aligns with existing research on technology-related self-efficacy [50,51], and people with a lower

SES perceived themselves and their environment as more susceptible to a cardiac arrest. This relationship is logical, as general health showed a strong correlation with SES.

Health variables, although often not included within behavior change models [10,28], seemed to play a meaningful role. First of all, medical professionals perceived greater benefits of a first responder app for OHCA than those outside the medical field, which aligns with expectations, given the app's potential to improve patient outcomes [6]. However, they also reported more barriers, lower self-efficacy, higher effort expectancy, and lower scores on facilitating conditions and perceived severity. This pattern of results, where medical professionals score lower on multiple variables associated with willingness to install the app, may be attributed to several factors. First, they may be less tech-savvy or more resistant to healthcare digitalization, a trend supported by previous research [52]. Second, their familiarity with the consequences of a cardiac arrest could reduce the perceived severity, as the nature of their work may lead them to view a cardiac arrest as a more routine, manageable event. Third, they may have reservations about the general public's ability to provide effective CPR, leading to greater skepticism toward the app's effectiveness in non-professional hands. This skepticism may be unfounded, as individuals trained in CPR scored higher across seven of the nine behavioral determinants in this study, highlighting the potential benefits of promoting CPR training among the general public in first responder app adoption.

Furthermore, the general health status of individuals affected the majority of the behavioral determinants but surprisingly this was not the case for having a cardiovascular disease. This is in contrast with the Health Belief Model which states that prior experience or direct contact with a health issue typically influence perceptions and attitudes towards related health behaviors [10]. Indeed, one would assume that individuals with a cardiovascular disease, given their increased susceptibility to a cardiac arrest, would perceive themselves as more at risk and potentially recognize greater benefits in a first responder app for OHCA. Although we did find individual correlations between having a cardiovascular disease and several determinants (e.g. positively related to effort expectancy, perceived susceptibility and perceived barriers), their significance diminished when tested within the full model. Given the cross-sectional nature of our study, making it impossible to make claims about directionality, longitudinal research is needed to further clarify these correlations. On the contrary, knowing people in your environment that have a cardiovascular disease heightened individuals awareness of personal risk and ensured more perceived benefits of a first responder app for OHCA.

Limitations

This study has several limitations that should be considered when interpreting the findings. First, as mentioned, the use of a cross-sectional survey design limits the ability to establish causal relationships. Longitudinal or experimental studies would offer a clearer picture of how all constructs within the model influence each other over time. Second, many of the behavioral determinants were assessed with only one or two items, which may lack the depth and reliability of multi-item scales and could reduce the accuracy of measuring complex constructs like self-efficacy. Finally, as there is no existing first responder app for OHCA in [country blinded], the study could not measure behavioral intention or actual app usage, which is typically measured in studies applying models like UTAUT or the Health Belief Model. This absence may limit the study’s applicability to contexts where first responder apps for OHCA are operational, as the factors influencing willingness to adopt the app may differ from those impacting intention or actual adoption.

Implications and Future Research

The findings of this study have both theoretical and practical implications. Theoretically, it finds its relevance in extending the UTAUT and Health Belief Model to altruistic mobile health apps that require active involvement, which has not been done before.

Moreover, this study contributes to the field by developing a comprehensive framework that also integrates relevant demographic and health variables, offering a more nuanced understanding of the factors influencing first responder app for OHCA adoption. Practically, this study was conducted in [country blinded], which is a country that currently lacks an established first responder system. As such, the knowledge provided by the study provides practical guidance regarding how to convince citizens in [country blinded] to participate in the first responder system that health care professionals are currently deploying. Building on this, future research could further enhance these efforts by designing and testing health messages in an experimental setting based on the key determinants of willingness to install a first responder app that we identified in the current study. In that way, subsequent studies can refine communication strategies for real-life campaigns. Additionally, it would be valuable to replicate the proposed model in countries where first responder apps for OHCA are already available. Such studies could examine actual adoption behaviors and compare the model's applicability across different contexts.

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Conflicts of Interest

None declared.

Abbreviations

CFI: comparative fit index

CPR: cardiopulmonary resuscitation

HBM: Health Belief Model

OHCA: out-of-hospital cardiac arrest

RMSEA: root mean square error of approximation

SES: socio-economic status

SRMR: standardized root mean square residual

TLI: Tucker-Lewer index

UTAUT: Unified Theory of Acceptance and Use of Technology

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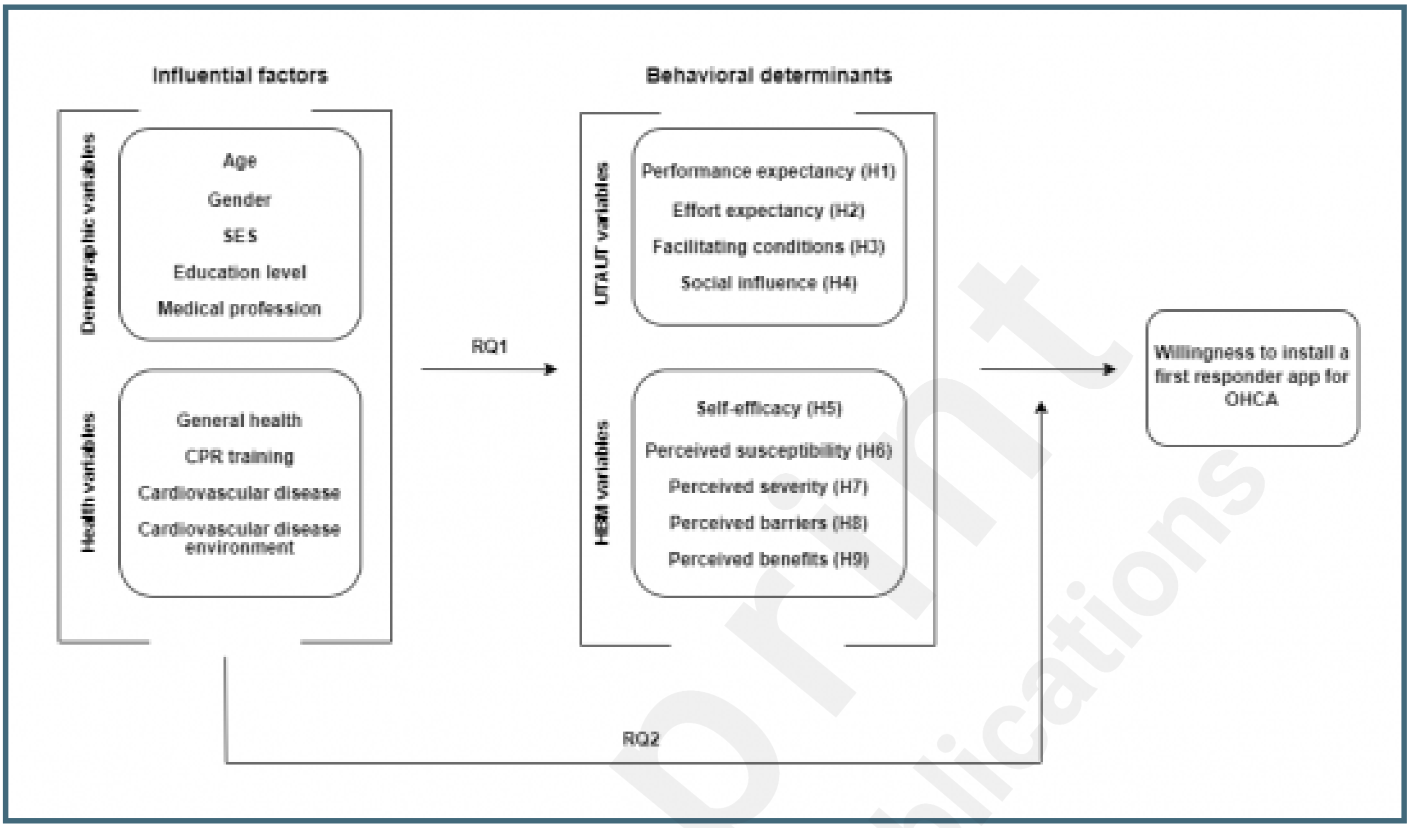
Supplementary Files

Figures

Conceptual framework of understanding and predicting willingness to install a first responder app for OHCA.



Multimedia Appendixes

Items of the behavioral determinants.
URL: http://asset.jmir.pub/assets/675104cd83678c4909be16dd1c71c57e.docx