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A mobile app for identifying individuals with undiagnosed diabetes and prediabetes (UDPD) and changing behavior: A two-year prospective study

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A mobile app for identifying individuals with undiagnosed diabetes and prediabetes (UDPD) and changing behavior: A two-year prospective study

Abstract

Background: To decrease the burden of diabetes in society, early screening of undiagnosed diabetes and prediabetes (UDPD) is needed. Integrating a diabetes risk score into a mobile app provides a useful platform to enable people to self-assess the risk of diabetes with ease.

Objectives: The objectives of this study were to: (1) assess the profile of app users of the Diabetes Risk Score (DRS) mobile app, (2) determine the optimal cut-off value of the Finnish diabetes risk score (FINDRISC) to identify UDPD in the Chinese population, (3) estimate the chance of developing diabetes within 2 years of using the app, and (4) investigate high-risk app users’ lifestyle behavior change after ascertaining their risk level from the app.

Methods: The study was divided into two phases. Phase 1 adopted a cross-sectional design. A descriptive analysis was performed on the app users’ profile. Cohen’s Kappa score was used to show the agreement between the risk level (as shown in the app) and HbA1c test results. Sensitivity, specificity, and area under curve were used to determine the optimal cut-off value of the DRS in this population. Phase 2 was a prospective cohort study, using an online survey to follow up the app users. Logistic regression model was used to estimate the chance of developing diabetes within 2 years after using the app. Paired t-tests were used to compare the high-risk app users’ lifestyle change.

Results: A total of 13,289 people used the app from 28 August 2014 to 31 December 2016. After data cleaning, 4,549 of these were considered as valid data. The majority of users were males, and about 40% had tertiary education or above. The optimal value of the DRS for identifying persons with UDPD was recommended to be 9, with an area under the ROC curve of 0.67 ($P < .01, 95\% CI: 0.60-0.74$), sensitivity of 0.70 (95% CI: 0.58-0.80), and specificity of 0.57 (95% CI: 0.47-0.66). At the 2-year follow up, people in the high-risk group had a higher chance of developing diabetes (OR 4.59, 95% CI: 1.01 to 20.81, $P = .048$) than the low-risk group. The high-risk app users improved their daily intake of vegetables (Baseline: $M = 0.76, SD = 0.43$; follow-up: $M = 0.93, SD = 0.26$; $t (81) =$
and daily exercise (Baseline: $M = 0.40$, $SD = 0.49$; follow-up: $M = 0.54$, $SD = 0.50$; $t(81) = -2.08, P = .04$).

**Conclusions:** The DRS app has been shown to be a feasible and reliable tool to identify persons with UDPD and predict diabetes incidence in 2 years. The app can also encourage high-risk people to modify diet habits and reduce sedentary lifestyle.

(443 words)
Introduction

Prevention of diabetes is at the top of the agenda for health promotion worldwide and in Hong Kong [1-3]. Target populations for diabetes prevention include those who have not been diagnosed and those who are in the stage of prediabetes [4]. Early detection of individuals with undiagnosed diabetes and prediabetes (UDPD) will enhance the implementation of lifestyle modification interventions, which have been shown to prevent the progression to diabetes or further complications [5]. It is estimated that 193 million people or nearly half of those with diabetes around the world are suffering from undiagnosed diabetes [6].

Mobile health (mHealth) has been used for different purposes in health promotion and maintenance. The proliferation of smartphones and software applications (or apps) has provided a new channel for health promotion, including recording of symptoms [7], smoking cessation [8], and weight control [7]. The advantage and convenience of the compact size and mobility of smartphones allows users to access health information and health assessment tools at any time and at any place that best suits individuals’ pace of living. A research study found that 75 million adults in the United States of America (USA) used their smartphones for health information and tools [9]. Among those aged 55 and older who own smartphones or tablets, half of them use the devices for health purposes [9]. The use of mobile apps has been evolving and becoming popular in Chinese society as mHealth is considered as not only trendy but also practical and layman-friendly. In Hong Kong, 12 free-of-charge health and fitness apps in the Android app market have been labelled as the most popular apps, and each app has more than 250,000 downloads [10]. However, scarce evidence about mHealth in assessing diabetes risk has been documented in the Chinese population.

Integration of a diabetes risk score into a mobile app is an innovative and potentially powerful tool for promoting diabetes self-assessment. Evidence has been shown that the Finnish Diabetes Risk Score (FINDRISC) has supported diabetes screening and prevention because of its cheap, easy to administer, convenient, and noninvasive features [11]. Lay people can easily use FINDRISC to assess their risk of developing diabetes, without any training. It is now being used in various European countries, including Finland, Belgium, Sweden, Greece, Germany and Spain [12-17]. Because of the
popularity, reliability and user-friendly nature of FINDRISC, the project team has chosen it as the key measurement of the DRS mobile app.

The DRS app was developed by a university project team comprised of a nursing faculty with rich experience in health literacy interventions, two family medicine experts, a professor in endocrinology, and a statistician. User tests were conducted by 22 Chinese adults in April 2013. Half of the participants of the user test had secondary education or above. Comments were collected from these app users on the clarity of the instructions given in the app, the logic of the sequence of the questions in the app, and the ease of data input by the participants. The app was then revised according to their comments. The DRS app (version 2) was officially launched on 28 August 2014 in a media interview in which 11 newspapers and one electronic media were included and reported its launch. The QR code of the app was posted on the university website to promote the app. This free-of-charge app could be downloaded from both the Google store (for Android devices) and the IOS App store (for iPad, iPhone) by searching the term “HKUDRS”.

The DRS app included the Chinese FINDRISC and questions related to lifestyle (such as smoking, drinking, dietary pattern, physical activity engagement). In the DRS app, the exact diabetes risk score was not shown, but the risk level was shown in a figure in which a pointer fell in one of the two colour zones, with red indicating high risk and green indicating low risk.

The objectives of this study were: (1) assess the profile of the app users of the DRS mobile app, (2) determine the optimal cut-off value of the diabetes risk score to identify UDPD in the Chinese population, (3) estimate the chance of developing diabetes within 2 years of using the app, and (4) investigate high-risk app users’ lifestyle behavior change after ascertaining their risk level from the app.

**Methods**

*The Two-Phase Study*

The whole study was divided into two phases. Phase 1 was conducted from Aug 2014 to Oct 2016, using a cross-sectional design. Phase 1a assessed the users’ profile, while Phase 1b assessed the appropriate cut-off value of the diabetes risk score to identify UDPD in the Chinese population. Phase
2 was conducted from October 3, 2016 to November 6, 2016 with a prospective cohort design. Phase 2a followed up the app users to estimate their chance of developing diabetes within 2 years. Phase 2b assessed the app users’ lifestyle changes after knowing their risk of diabetes from the app.

**Samples**

Since this is a free app in the app stores, anyone who was capable of accessing the Internet and app stores and reading and understanding Chinese could download the app to their mobile phones. On the first screen of the app, we indicated that it was developed for research purposes, and its use implied that users agreed to join the research study and consented to the project team using their data in aggregate manner for research purposes and future analysis. Those who met the following criteria were included in the analysis in Phase 1a: 1) aged 18 years or over, and 2) their phone numbers indicated the country code 852 (for Hong Kong). Subjects in Phase 1b were selected from Phase 1a and met the following criteria: 1) provided phone or email addresses in the app and agreed to allow the project team to approach them; 2) had never been diagnosed with diabetes (of any kind); and 3) willing to attend a comprehensive health assessment (including blood taking) in a university campus. Subjects in Phase 2 were those who: 1) used the DRS app in 2014 and 2015, 2) provided email addresses in the app, and 3) were willing to complete an online survey. Those with known diabetes in 2014/15 or those who used the app less than one year from the time we conducted the online survey were excluded.

**Procedures**

Phase 1a: Since the launch of the app, the project team periodically monitored the number of downloads and ensured that the app was downloadable from the app stores. For the sake of protecting privacy, only the Principal Investigator (PI) had right of access to the server. Before passing the data to the trained research assistant for data cleaning and to develop the database for this study, the PI removed all app users’ personal data to protect privacy.

Phase 1b: We sent emails to the app users and invited them to receive a 1-hour comprehensive health assessment in the university campus between June and August 2015. The inclusion criteria were stated clearly in the invitation emails, and the app users replied to the emails and indicated their
willingness to join the health assessment. In the assessment, a research nurse took 5ml venous blood from each participant. The blood samples were sent to the laboratory of a regional public hospital in which HbA1C was measured by high-performance liquid chromatography (Biorad Variant II Turbo). According to the American Diabetes Association, HbA1C ≥6.5% is considered as “diabetes”, while 6.5%>HbA1C ≥5.7% is considered as prediabetes [18].

App users with HbA1C levels higher than 6.5% were informed by the project team by phone and encouraged to consult their family doctors. This was done for ethical reasons, so that the app users with abnormal readings were not placed at a disadvantage by not receiving necessary treatments.

Phase 2a and 2b: We sent invitation emails to the app users and encouraged them to complete a follow-up questionnaire from October 3, 2016 to November 6, 2016. Diabetes incidence was recorded when the app users self-reported of having diabetes in the said period. If the app users were diagnosed with diabetes, they were asked to provide the dates of receiving diagnosis (month and year).

**Statistical Analyses**

Replicated inputs, incomplete inputs, or inputs that were exactly the same as default figures in blood pressure, body height and body weight were considered as invalid inputs and excluded in the analysis. Descriptive statistics, including means, standard deviations, frequencies, and percentages were computed to present the subjects’ socio-demographic information and the distribution of diabetes risk scores. In Phase 1b, Receiver Operating Characteristic (ROC) curves analysis was used to determine the optimal cut-off level of DRS scores with reference to the usual clinical practice for suspecting the risk of diabetes (or the stage of prediabetes) in Hong Kong. The optimal cut-off point of the DRS score was also determined by the sensitivity, specificity, maximum value of Youden’s index, and Cohen’s Kappa of the DRS with reference to the agreement with HbA1c. Cohen’s kappa values equal to or lower than zero indicated no agreement, 0.01-0.20 as none to slight, 0.21-0.40 as fair, 0.41-0.60 as moderate, 0.61-0.80 as substantial, and 0.81-1.00 as almost perfect agreement [19].

In Phase 2a, multiple logistic regression models were used to examine the odds ratio (OR) of diabetes incidence between the high-risk group and the low-risk group (classified by the recommended FINDRISC cut-off value found in Phase 1b). Educational level is a confounder in
diabetes. Many studies have proved that people with a higher educational level have a better lifestyle in their daily lives, and people with a healthy lifestyle will have less risk of developing diabetes in the future [20]. A meta-analysis also demonstrated that higher educational levels were consistently associated with lower incidence of diabetes [21]. As sex and education were correlated, we adjusted both sex and education in the regression models. The Hosmer and Lemeshow test was used to assess the goodness of fit for logistic regression models. The model fits the data well when the $P$ value is greater than 0.05 [22]; this implies the model has acceptable fitness.

In Phase 2b, paired t-tests were applied to compare the means of lifestyle variables at the baseline with the ones in the follow-up for the high-risk group. The data was analyzed using the Statistical Package for the Social Sciences (SPSS) version 22.0 for Windows (SPSS, Inc., Chicago, IL, USA).

**Results**

Principal findings

*Phase 1a: The profile of DRS app users*

Data was collected in the period of 28 August 2014 to 31 December 2016. A total of 13,289 Chinese residents downloaded the HKU DRS app and self-assessed the risk. After data cleaning, 4,549 were considered as valid data in Phase 1a. 69.71% were Android users and the rest were iPhone users. Table 1 shows the demographics of the app users in all phases. The majority of app users (60.2%) were males. 29.2% of them were aged 55-64 and 35.3% were aged 65 or above. Nearly two-fifths of the app users had tertiary education or above (42.0%). The mean (SD) diabetes risk score was 9.10 (4.85). 22.88% were shown to be at risk of developing diabetes.
Table 1. Demographics of the app users of the Diabetes Risk Score mobile app

<table>
<thead>
<tr>
<th>Variables</th>
<th>Phase 1a (n=4,549)</th>
<th>Phase 1b</th>
<th>Phase 2a and 2b (n=127)</th>
<th>Phase 2a and 2b (n=199)</th>
<th>P</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>HbA1C &lt;5.7% (n=109)</td>
<td>HbA1C ≥5.7% (n=79)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Sex</td>
<td>Male</td>
<td>60.2%</td>
<td>60.6%</td>
<td>63.3%</td>
<td>.62</td>
</tr>
<tr>
<td></td>
<td>Female</td>
<td>39.8%</td>
<td>39.4%</td>
<td>36.7%</td>
<td></td>
</tr>
<tr>
<td>Age</td>
<td>≤44</td>
<td>22.1%</td>
<td>12.9%</td>
<td>5.1%</td>
<td>.43</td>
</tr>
<tr>
<td></td>
<td>45-54</td>
<td>13.4%</td>
<td>41.3%</td>
<td>39.2%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>55-64</td>
<td>29.2%</td>
<td>37.6%</td>
<td>45.6%</td>
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</tr>
<tr>
<td></td>
<td>≥ 65</td>
<td>35.3%</td>
<td>8.3%</td>
<td>10.1%</td>
<td></td>
</tr>
<tr>
<td>Educational level</td>
<td>Primary or below</td>
<td>20.1%</td>
<td>1.8%</td>
<td>5.1%</td>
<td>.76</td>
</tr>
<tr>
<td></td>
<td>Secondary</td>
<td>37.9%</td>
<td>57.8%</td>
<td>62.0%</td>
<td></td>
</tr>
<tr>
<td></td>
<td>Tertiary or higher</td>
<td>42.0%</td>
<td>40.4%</td>
<td>32.9%</td>
<td></td>
</tr>
</tbody>
</table>

Note. DRS stands for diabetes risk score; It refers to the Finnish Diabetes Risk Score (FINDRISC)
**Phase 1b: Determining the optimal value of DRS for identifying people with UDPD**

A total of 972 people left their contacts to the project team and were included in the invitation in this phase. Only 210 participants (21.6%) agreed to attend the health assessment. Of these, 22 people who had type 1 or type 2 diabetes were excluded from the study, so eventually only 188 app users were included in the analysis. The majority of participants aged between 45 and 64 years old (81.4% and 61.7%) were males. These app users had a relatively higher educational level than the general public, with over 90% of participants reporting secondary school or higher qualifications [23].

**Results of HbA1C tests**

Among the 188 participants who participated in blood tests, 79 (42.0%) had HbA1C ≥5.7%. Thus, they were considered as persons with undiagnosed diabetes or prediabetes. Of these, 14 participants’ (17.7%) HbA1C was even higher than 6.5% and they were considered as having undiagnosed diabetes. There was no significant difference in age, sex, and educational level between app users with UDPD and those with normal HbA1c level (Table 1).

**Optimal Cut-off value for DRS in Chinese population**

Table 2 shows the sensitivity and specificity of various FINDRISC scores in relation to UDPD. The sensitivity and specificity of a FINDRISC score > 8 were 0.70 (95%CI: 0.58-0.80) and 0.57 (95%CI: 0.47-0.66) respectively, with PPV of 0.54 (95%CI: 0.44-0.64) and NPV of 0.72 (95%CI: 0.61-0.81). A FINDRISC >8 also had the greatest Youden index of 1.27. When using a FINDRISC >9, specificity increased to 0.62 (95% CI: 0.53 to 0.72), sensitivity decreased to 0.61 (95% CI: 0.49 to 0.72), the Youden index also decreased to 1.23. The area under ROC curve (AUC) of a FINDRISC score >8 was 0.67 (95%CI: 0.60-0.74, P < .01) (Figure 1). This suggested that a FINDRISC score >8 had sufficient properties for identifying persons with UDPD. We have considered other values such as FINDRISC score >9; however, the sensitivity of this score decreased dramatically to 0.61. Therefore, we would recommend a FINDRISC score = 9 as the optimal cut-off point for identifying UDPD in a Chinese population.
Table 2. Characteristics of the Finnish Diabetes Risk Score (FINDRISC) using different cut-off values to predict undiagnosed diabetes and prediabetes (UDPD)

<table>
<thead>
<tr>
<th>FINDRISC cut-off values</th>
<th>Incident UDPD (HbA1C ≥ 39 mmol/mol, 5.7%)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Sensitivity (95% CI)</td>
</tr>
<tr>
<td>&gt; 6</td>
<td>0.78 (0.68-0.87)</td>
</tr>
<tr>
<td>&gt; 7</td>
<td>0.75 (0.64-0.84)</td>
</tr>
<tr>
<td>&gt; 8</td>
<td>0.70 (0.58-0.80)</td>
</tr>
<tr>
<td>&gt; 9</td>
<td>0.61 (0.49-0.72)</td>
</tr>
<tr>
<td>&gt; 10</td>
<td>0.52 (0.40-0.63)</td>
</tr>
<tr>
<td>&gt; 11</td>
<td>0.41 (0.30-0.52)</td>
</tr>
</tbody>
</table>

Note. UDPD: undiagnosed diabetes and prediabetes

PPV: positive predictive value

NPV: negative predictive value
Figure 1. Receiver operating characteristic (ROC) curve of the FINDRISC value (>8)

Receiver Operating Characteristic (ROC) curve analysis of the performance of the Finnish Diabetes Risk Score (FINDRISC) in identifying undiagnosed diabetes and prediabetes. The area under the ROC was 0.67 (95% CI 0.60-0.74). When the FINDRISC cut-off value was greater than 8, its sensitivity was 0.70 (95% CI 0.58-0.80) and specificity was 0.57 (95% CI 0.47-0.66).

**Phase 2a: Estimating the chance of developing diabetes within 2 years**

In Phases 2a and 2b, 326 app users replied to the invitation emails and completed the online survey. Nearly half of the app users were aged 65 or over (44.2%), and only 8.3% of participants were aged 44 or younger. The majority of the app users were males (62.6%). Regarding their educational level, 41.7% of the app users had secondary qualifications and 40.2% had tertiary qualifications or higher. Among these, 199 app users (61.0%) were considered as the high-risk group when DRS ≥ 9 was applied. People in the high-risk group were older than those in the low-risk group (P < .001) (Table 1). There was no significant difference in sex and educational level between the two groups.

The mean follow-up time of the app users was 22.66±5.83 months. After nearly a 2-year follow-up, 15 participants developed diabetes. The mean time of diagnosis of diabetes during follow-up was 12.93±8.28 months, range 1 to 25 months. The incidence rate of diabetes was 25.56 per 1000 person
years. For the high-risk group, the incidence rate of diabetes was 36.50 per 1000 person years. For the low-risk group, the incidence rate of diabetes was 8.59 per 1000 person years. Fisher’s Exact Test showed that the association between the risk groups and diabetic incidence was marginally insignificant ($P = 0.055$).

Table 3 shows the association between the risk groups and diabetes incidence. In Model 1 (the unadjusted logistic regression model), there was a marginally insignificant association between the risk groups and diabetes incidence (OR: 4.37, 95% CI: 0.97 to 19.69, $P = 0.055$). However, in Model 2, after adjusting for sex and educational level, app users in the high-risk group had a significantly higher chance of developing diabetes (OR: 4.59, 95% CI: 1.01 to 20.81, $P = 0.048$) compared to the low-risk group. The Hosmer and Lemeshow test gave a p-value of 0.905 which implied the regression model had an acceptable fitness.
Table 3. Logistic regression model of diabetes incidence between the high-risk app users and low-risk app users

<table>
<thead>
<tr>
<th></th>
<th>Model 1</th>
<th>Model 2</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Odds Ratio</td>
<td>95% CI</td>
</tr>
<tr>
<td>Diabetes risk group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>High</td>
<td>4.37</td>
<td>0.97 to 19.69</td>
</tr>
<tr>
<td>Low (ref)</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Sex</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Male</td>
<td>1.21</td>
<td>0.38 to 3.88</td>
</tr>
<tr>
<td>Female (ref)</td>
<td>1</td>
<td></td>
</tr>
<tr>
<td>Educational level</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Primary or below</td>
<td>1.33</td>
<td>0.42 to 4.31</td>
</tr>
<tr>
<td>Secondary</td>
<td>0.96</td>
<td>0.19 to 5.00</td>
</tr>
<tr>
<td>Tertiary or higher (ref)</td>
<td>1</td>
<td></td>
</tr>
</tbody>
</table>
Phase 2b: Lifestyle changes among the high-risk app users

The app users who were informed that they had a higher risk of developing diabetes improved their daily intake of vegetables (Baseline: M = 0.76, SD = 0.43; Follow-up: M = 0.93, SD = 0.26; t(81) = -3.77, P < .001) and daily physical activities (Baseline: M = 0.40, SD = 0.49; Follow-up: M = 0.54, SD = 0.50; t(81) = -2.08, P = .04). However, no significant change was found in their smoking status (Baseline: M = 0.15, SD = 0.36; Follow-up: M = 0.09, SD = 0.28; t(81) = 1.92, P = .06) or their alcohol consumption (Baseline: M = 0.07, SD = 0.26; Follow-up: M = 0.04, SD = 0.19; t(81) = 1.35, P = .18).

Discussion

This study reported the development of a mobile app for identifying people with UDPD and its use over a period of 2 years. Both Android and iPhone users found this app accessible, and more than 13,000 people had downloaded and used this app. Although only app users in Hong Kong were included in the analysis, we noted that quite a number of downloads were from countries in Asia, America and Europe. This showed the potential for expanding the use of this mobile app to people who can read and understand Chinese around the world. To the best knowledge of the project team, this app was the first DRS app targeted at a Chinese population for diabetes risk self-assessment in 2014. The American Diabetes Association recommends that screening for diabetes should be carried out at 3-year intervals after the age of 45 years, particularly for those are overweight (whose BMI is 25 kg/m² or higher) [24]. However, not many people comply with this recommendation [25]. As many people are reluctant to go for blood tests, this DRS mobile app provides the general public a means for self-assessment before consulting doctors.

This DRS app, adopting FINDRISC as the key measure for estimating diabetes risk, has been shown to be a reliable tool, although it cannot replace diagnostic investigations such as the Oral Glucose Tolerance Test, HbA1c and clinical judgement. Validated with HbA1c, this DRS app performed well in detecting people with UDPD. The recommended optimal cut-off point of FINDRISC for people with UDPD was 9. The sensitivity and specificity of the recommended cut-off points are reasonably good. Nearly 70% of persons at high risk of diabetes can be identified with the
new recommended cut-off points in this DRS app. Approximately 1 million of the Hong Kong population were not aware of their undiagnosed diabetic and prediabetic status [26]. If they use this app, which has a sensitivity of 70%, at least 0.7 million of them could know their risk earlier and could start preventive actions.

The new recommended optimal cut-off value of FINDRISC in the DRS app was comparable with the cut-off values in other populations (Appendix 1), although there was a slight difference [27-29]. In the United States, the optimal cut-off value of FINDRISC for identifying undiagnosed diabetes was 11 [29], while in Bulgaria the cut-off point was recommended as 12 (there was no differentiation between genders) [28], and in Colombia it was 14 (for both men and women) [27]. Our finding was similar to the recommended cut-off point in a study in Isfahan, but the specificity of the recommended point in the current study was much higher than the one shown in the Isfahan population [30]. Variations in the recommended cut-off points in different populations may be related to the variation of referenced tests. In these studies, a variety of blood tests (Oral Glucose Tolerance Test, OGTT; fasting blood glucose and HbA1c) were used. Although the cut-off values vary, most of the recommended points are within a reasonable range of scores, as suggested by the original developers of FINDRISC [11]. The findings of the current study therefore provide additional information about the cut-off value of FINDRISC in the Chinese population.

In this prospective study, two important pieces of evidence were worth noting. Firstly, this DRS app has not only concurrent but also a predictive nature (indicating the chance of developing diabetes in the next 2 years). Evidence was shown that app users in the high-risk group had a significantly higher chance (4.59 times) of developing diabetes than those in the low-risk group. This finding echoed the findings of previous studies in other populations. In Colombia, the risk of incidence of type 2 diabetes in one year among participants with high risk scores was 4.8 times that among the low-risk group [27]. Similar results were also found in another longitudinal study by Janghorbani et al., the risk of diabetes in the second quartile (9≤FINDRISC<13) being 4.3 times that of participants in the lowest quartile (FINDRISC<9) [30]. These results showed that FINDRISC in the mobile app was a useful tool for predicting the incidence of diabetes in the Chinese population.
Secondly, the app encouraged people to change their lifestyle. The app users who were informed of having a high risk of developing diabetes by the DRS app significantly improved their daily intake of vegetables and did more physical activities in the follow-up period. This showed that the DRS app was a practical tool in health promotion for the general public. The app users seemed to be more cautious about their lifestyles and started to develop healthier habits that could protect them from serious health problems like diabetes [31].

Some researchers have developed different sets of diabetes risk score models for the Chinese population in recent years. Tian and team (2017) developed the Dagang dysglycemia risk score model to identify undiagnosed prediabetes and diabetes for the oil field working-age population [32]. Another risk score model for detecting type 2 diabetes for a rural adult Chinese population was developed by Zhang and colleagues [33]. Although these two risk models have high AUCs (0.791 and 0.766 respectively), both models consist of invasive items (such as blood taking) and therefore are not recommended to be used in mobile apps. A simpler and non-invasive diabetes risk score was developed based on age, waist circumference, and family history of diabetes for undiagnosed diabetes [34]. Nonetheless, its specificities were rather low (0.211 in men and 0.436 in women). Considering the availability of diabetes risk score models, FINDRISC seemed to be an appropriate measure to adopt in a mobile app.

**Limitations**

This study has some limitations that need to be addressed. First, we used only the HbA1C test as the diagnostic standard to identify people with UDPD; however, the 75-g oral glucose tolerance test (OGTT) is the gold standard for diagnosing diabetes. We considered HbA1C because it was more convenient and time saving than OGTT. Secondly, the BMI and waist circumference cut-off values used in the calculation of FINDRISC were for Caucasians [15]. These cut-off values might not be the optimal values for Asian populations, which might have affected the sensitivity of the FINDRISC model. Therefore, future studies could revise the BMI and waist circumference cut-off values to ones that are optimal for Asian people. Thirdly, interpretation of diabetes incidence should be cautious. Incidence rate of diabetes was determined based on the self-reported diabetes at follow-up.
assessment. Subjects with undiagnosed diabetes might report themselves as ‘non-diabetic’, or it is possible that subjects may be diagnosed much earlier than the follow-up assessment time, this may cause detection bias and interval-censored bias. We could not directly communicate with the respondents of the online survey or perform body measurements or blood tests after the online survey. Future studies could use blood samples to validate the incidence of diabetes.

Implications for future research

Future studies could explore the existence of other predictors like dietary sodium, beverage and fat intake to improve the predictive validity of FINDRISC in the Chinese population. Predictors of diabetes have been used to modify FINDRISC. Studies in Germany and the Philippines modified and simplified FINDRISC for their populations [13, 35]. Secondly, the determination of different cut-off values of FINDRISC for different socio-demographic groups could make the classification of UDPD more accurate for different groups of people. Subgroup analysis has been performed in many other FINDRISC validation studies. Studies in the U.S., Colombia, and other countries set up different cut-off scores for different groups according to sex, age or ethnicity [27, 29]. The results of the current study indicate that educational level was one of the covariates of risk score groups and diabetes. Therefore, future studies involving a larger population sample and focusing on educational level are required to identify the FINDRISC cut-off scores in different sociodemographic groups in the Chinese population.

Conclusion

This DRS app was a reliable tool for identifying persons who have undiagnosed diabetes or prediabetes. The odds of developing diabetes were much higher among the high-risk app users than among the low-risk users, evidencing the predictive power of the app in diabetes incidence. The app can also encourage high-risk app users to modify their lifestyle for the sake of reducing the progression from pre-diabetes to diabetes. This is an illustration of the use of mobile app in health promotion and disease prevention.
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Conflict of Interests

The authors declare that they have no competing interests.

Abbreviations

AUC: Area under the Receiver Operating Characteristic Curve  
BMI: Body Mass Index  
DRS: Diabetes Risk Score  
FINDRISC: Finnish Diabetes Risk Score  
HbA1c: glycated haemoglobin  
OGTT: Oral Glucose Tolerance Test  
ROC: Receiver Operating Characteristic  
UDPD: Undiagnosed Diabetes and Prediabetes

Authors’ contribution

AYM Leung contributed to the study design, data analysis, interpretation of the findings, intellectual input, and revision of the manuscript. X Xu and MKT Cheung contributed to data collection, data analysis, interpretation of the findings and drafting of the manuscript. Both authors read and approved the final manuscript. PH Chau, EYT Yu, J Wong contributed to study design, data analysis and interpretation of the findings. CKH Wong and DYT Fong contributed to data analysis and interpretation of the findings. CLK Lam contributed to study design, intellectual input and revision of the manuscript.

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Ethics approval and consent to participate

Approval was obtained from the Institutional Review Board of the University of Hong Kong/Hospital Authority Hong Kong West Cluster (HKU/HA HKW IRB). Consent form was embedded on the first screen of the app. App users clicked a button on the app to indicate their consent to join the study.

Multimedia Appendix 1:

Different Finnish Diabetes Risk Score (FINDRISC) cut-off values for the detection of undiagnosed diabetes, pre-diabetes and hyperglycemia in different populations
References


