

Stroke Riskometer™ mobile phone application improves stroke knowledge in a randomized controlled trial

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Abstract

Background: Increasing knowledge about stroke may reduce its burden. We examined the effect of the Stroke Riskometer™ mobile phone application (the App) on stroke knowledge in a randomized controlled trial (RCT).

Methods: This was a pre-specified secondary outcome analysis in a phase III, prospective, participant and outcome assessor-blinded, two-arm RCT in Australia and New Zealand. Participants were recruited between 2021 and 2023, aged 35–75 years, with ≥ 2 stroke risk factors and no cardiovascular disease history. Participants were randomized after assessment of stroke risk factors and knowledge to the intervention group (IG—received risk factor assessment by email and links to the App), and the usual care group (UCG—received risk factor assessment with links to generic information by email). Stroke knowledge was measured at baseline, 3, 6, and 12 months using six validated questions (total score 0 (low knowledge) to 19 (high knowledge)). We used linear and logistic mixed-effects modeling to assess differences in the level of overall stroke knowledge and domains (description, warning signs, risk factors, management) between IG and UCG at each time point. Effect modification of the intervention with age, sex, level of education, ethnicity, socioeconomic status (SES), and country was assessed.

Results: There were 862 participants (mean age: 58.1 years (standard deviation (SD): 10.8), 63.0% female, 61.6% tertiary educated, 73.3% European, and 14.7% most disadvantaged area-level SES) randomized to IG (n=429) and UCG (n=433). Dropouts (IG/UCG) were as follows: 7.9%/4.8% at 3 months, 3.0%/1.8% at 6 months, and 13.5%/9.0% at 12 months. The time-IG interaction showed a statistically significantly increased overall stroke knowledge ($\beta = 0.50$, 95% confidence interval (CI) = 0.02, 0.97) compared with UCG at 6 months only. The intervention effect was stronger in tertiary educated, non-European, and non-Indigenous ethnic groups, and the least disadvantaged SES group. For domains, IG was more likely to correctly identify stroke risk factors (odds ratio (OR) = 1.92, 95% CI = 1.09, 3.39) at 3 months, compared with UCG.

Conclusion: The Stroke Riskometer™ App modestly improved stroke knowledge compared with UCG at 6 months but lacks evidence for retaining knowledge at 12 months. As knowledge can drive behavior change, the App may be a tool to enhance primary stroke prevention.

Trial registration: ACTRN12621000211864.

Keywords

Health knowledge, mobile applications, primary prevention, risk factors, Stroke Riskometer™ app, stroke

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Introduction

Globally, stroke remains the second leading cause of death and the third leading cause of death and disability combined.¹ Approximately 90% of the population-attributable risks of stroke are due to 10 modifiable risk factors, which are shared across many non-communicable diseases.² The most effective way to reduce the burden of stroke is through primary prevention; however, current prevention strategies are not adequately effective.³ Low community awareness of stroke is among the major barriers to preventing stroke.⁴ Knowledge of stroke warning signs and risk factors can affect stroke risk reduction and timely presentation to the hospital.⁵ According to the knowledge–attitude–behavior model, health behaviors change via a continuous process: acquiring knowledge, developing attitudes, and forming behaviors.⁶ As such, health awareness can serve as the initial step toward behavioral change in modifiable stroke risk factors.⁷

mHealth may enhance primary stroke prevention by improving access at low costs.⁸ In a meta-analysis, improvements in glycemic control and smoking cessation at 6 months were found among mHealth interventions mostly incorporating text messaging.⁹ mHealth also includes mobile phone applications (e.g. apps) that can leverage the multimedia tools in smartphones. However, there is limited empirical evidence supporting mHealth apps for primary stroke prevention. The Stroke Riskometer™ mobile phone application is an mHealth solution that provides a personalized stroke risk assessment based on an individual's demographic and health information and gives motivating, brief education to reduce risk, incorporating behavior-change strategies.¹⁰

Several pilot studies have provided evidence that the App changes stroke awareness. In a pilot RCT in New Zealand, the proportion of participants showing awareness of ≥ 2 symptoms improved by 13% in App users but reduced by 8% in the control group at 6 months.¹¹ Another pilot study in Ghana and Nigeria revealed that a 2-month intervention including the Afrocentric Stroke Riskometer™ App improved stroke risk awareness by 16.1% compared

to 8.9% increase in the control group among stroke-free individuals.¹² Overall, given the evidence about the App in pilot studies, a full-scale RCT is justified. Therefore, as part of the PERsonalized Knowledge to reduce the risk of Stroke (PERKS-International) RCT that had a primary outcome of the change in Life's Simple 7 risk factor score,¹³ we aimed to determine the effect of the App on the pre-specified secondary outcome of stroke knowledge in the IG compared with the UCG at baseline, 3, 6, and 12 months post-randomization in people with two or more stroke risk factors.

Methods

Study design

This study was part of a phase III, prospective, pragmatic, double-blinded, endpoint, and two-arm RCT conducted in Australia and New Zealand. Mobile network with 4G covers more than 96% of the population, meaning that mHealth applications can work effectively in both rural and urban areas of both countries. PERKS-International RCT was registered on the Australian New Zealand Clinical Trials Registry on 1 March 2021 (ACTRN12621000211864), and the protocol was published.¹³

All participants provided written informed consent before participation (see Supplemental Material). This RCT is reported per the updated Consolidated Standards of Reporting Trials (CONSORT) 2025 guideline¹⁴ (Supplemental Table 1); template for intervention description and replication checklist was used to report the intervention¹⁵ (Supplemental Table 2), and guidelines for reporting of health interventions using mobile phones: mHealth evidence reporting and assessment checklist¹⁶ (Supplemental Table 3). Two people with lived experience of stroke were involved in the development and implementation of the trial. One person was the chair of the Scientific Advisory Committee, who provided oversight for the trial, and the other person was an investigator on the overarching grant (Synergies TO Prevent stroke (STOPstroke)) that funded this RCT.

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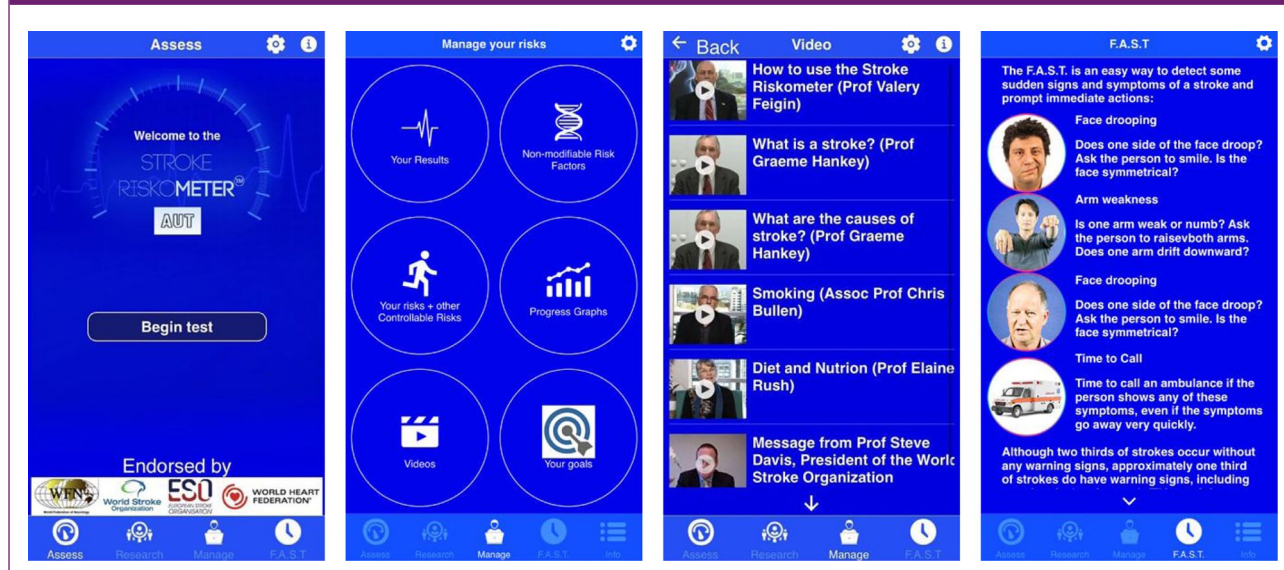
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Figure 1. Screenshots of the Stroke Riskometer™ mobile phone application.

Recruitment

Participants were recruited between August 2021 and November 2023 using internal and external recruitment strategies. Internal strategies (posters, flyers, and social media advertisements) were employed until October 2022. External strategies (clinical trials recruitment agency and primary health organizations) were implemented from November 2022 to November 2023.

Participants

Inclusion criteria were people aged ≥ 35 and ≤ 75 years, having at least two “poor” risk factors self-reported at screening according to LS7 criteria,¹⁷ own a Smartphone, have a Montreal Cognitive Assessment score ≥ 26 ,¹⁸ able to speak English, understand requirements of the study, familiar with the use of mobile phone applications, understand the information provided through a mobile phone application, and give informed consent. Exclusion criteria were life-threatening conditions with a life-expectancy < 5 years, participating in another RCT, a history of stroke or myocardial infarction, and family or household members of existing participants, as outlined in the protocol.¹³

Randomization

Participants were randomized to the IG and UCG in a 1:1 ratio using a computer-generated block randomization procedure with recruitment site (Auckland, Hamilton, Melbourne, Adelaide, or Hobart) as a stratification factor.

Blinding

The RCT was double-blinded. To prevent contamination of the UCG, the study was advertised solely as involving education, including by mobile phone. Recruitment materials did not refer to the App (Supplemental Material: participant information sheet, pages 8–17).

Intervention group—Stroke Riskometer™ app

Participants randomized to the IG were sent an email providing a link to the iTunes App Store or Google Play to download the App for free. The email included videos showing how to download and use the App, complete the stroke risk assessment, and interpret the results (Supplemental Material, pages 19–20). The App was designed for use by the general population and has been freely available on the Apple App and Google Play Store since 2014 (Figure 1). Users can download and share their results with healthcare providers. The App’s main functions are calculating 5- and 10-year stroke risk using a validated algorithm¹⁹, providing education and feedback, sending push notifications, and tracking risk factors (Supplemental Material, page 21). Based on this personalized risk assessment, the App provides information on how to lower the likelihood of having a stroke through a “Manage” section based on the individual’s non-modifiable and modifiable risk factors. The App mostly provides education on stroke risk factors and their management (32 sections and 3 videos), with some information on stroke, including symptoms (1 section and 3 videos).

Usual care group

Participants in the UCG were not informed about the App. They received one email after randomization that contained their risk factor assessments as per the American Heart Association's LS7 score with links to online evidence-based information about stroke prevention (Supplemental Material, page 22). The procedures used to encourage follow-up completion in the IG were also used for the UCG.

Measures and data collection

Baseline characteristics of the participants. Baseline details included age, sex, level of education, ethnicity, area-level SES, and country of residence.

Outcome measures. IG and UCG received online assessments at 3 and 12 months, along with face-to-face assessments at baseline and 6 months (see Supplemental Material, page 23 and Table 4). This pre-specified analysis focusing on a secondary outcome of stroke knowledge comprised four domains (description, warning signs, risk factors, management of stroke) at baseline, 3, 6, and 12 months, assessed using a validated questionnaire in previous studies.^{11,20} Six questions were used to assess stroke knowledge: three on stroke description (6 options, 2 correct answers), warning signs (7 options with 3 correct answers), and risk factors (13 options, 11 correct answers), and three on stroke management (6 options, 1 correct answer for each question, with a total of 3 correct answers). See Supplemental Table 5 for full details. For scoring, each correct response received one point, while incorrect responses received zero points, with the total score ranging from 0 to 19; higher scores indicate greater stroke knowledge. There was high internal consistency (Cronbach's alpha (α) = 0.88).

Sample size

The sample size calculation was based on the primary outcome, aiming to recruit 850 people for a sample size of 790 participants. This provided 80% power (two-sided α = 0.05) to detect the effect of the App at 6 months based on differences in the LS7 score in the New Zealand pilot (0.40, SD = 1.61) (11), assuming a 10% dropout.¹³

Statistical analysis

Descriptive statistics comprised frequency and percent to summarize categorical variables, and means and standard deviations (SD) to summarize continuous variables. Both unadjusted and adjusted linear mixed-effects models assessed differences in the level of stroke knowledge between the IG and UCG at baseline, 3, 6, and 12 months post-randomization in main and per-protocol analyses. Linear mixed-effects models handle missing data under the

assumption of "missing at random" without multiple imputation.²¹ The main analysis included all participants by allocated group, while the per-protocol analysis excluded those with protocol violations.

Major protocol violations determined by the Steering Committee were as follows: (1) those not downloading or using the App based on responses to the user data, 1-week and 6-month surveys; (2) assessed by a research assistant who was unblinded to the treatment allocation; (3) in the UCG and potentially unblinded due to an administrative error; and (4) lost to follow-up or had incomplete outcome data at 6 months. Interaction terms were included in the linear mixed-effects model to evaluate whether the intervention effect varied by pre-specified groups of age, sex, level of education, ethnicity, SES, country of residence, and an exploratory group of baseline LS7 risk factor category. In addition, exploratory analysis was conducted to assess differences in stroke knowledge at each time point among participants in the IG who shared their App data with the UCG, using a linear mixed-effect model to evaluate the potential effect of intervention fidelity on outcome.

A post hoc exploratory analysis examined the differences in stroke knowledge domains between the IG and UCG at baseline, 3, 6, and 12 months post-randomization. Dichotomous variables for each domain (description, warning signs, risk factors, and management) were created based on whether a person answered all questions correctly (Supplemental Table 6). Mixed-effects logistic regression assessed the differences in knowledge in each domain after adjustment for participant age, sex, level of education, ethnicity, SES, and country of residence in the main, per-protocol, and subgroups. Analyses were conducted in Stata version 18.0, and a $p \leq 0.05$ was considered statistically significant.

Results

A total of 3441 participants participated in the online screening, whereby 1698 completed it and could be assessed for eligibility. Of these, 862 participants were randomized (Figure 2).

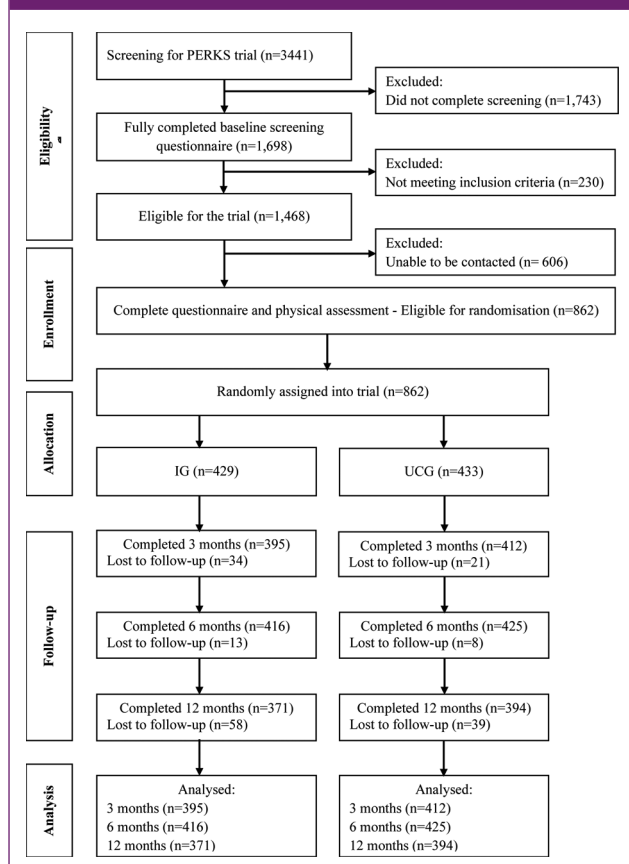
Baseline characteristics of participants

Baseline characteristics were well balanced between IG and UCG, with the exception of SES; IG had more participants in the most disadvantaged area than UCG (Table 1).

Fidelity of the intervention

At 1 week post-randomization, 64% of the participants in the IG self-reported downloading the App, and 62% reported having used the App. We estimate 21% of participants in the IG did not download or use the App within 6 months (Supplemental Materials, page 27 and

Figure 2. CONSORT flow diagram illustrating the PERKS-International RCT process to determine the effect of the Stroke Riskometer™ mobile phone application on stroke knowledge. IG, Intervention group; UCG, usual care group.



Supplemental Table 7 for full details), with 31% ($n=133$) sharing their App data. No participants in the UCG reported using the App in an unprompted question at the 6-month assessment about health apps they used.

Differences in overall stroke knowledge at each time point

In the main and per-protocol analysis, the mean stroke knowledge scores for IG consistently increased from baseline to 6 months but then declined slightly at 12 months. In UCG participants, knowledge increased from baseline to 3 months, remained stable at 6 months, and increased again at 12 months (Figure 3).

In the main analysis, the interaction of time by IG significantly increased the stroke knowledge score by 0.50 points ($\beta=0.50$, 95% confidence interval (CI)=0.02, 0.97) compared with UCG at 6 months but not at other time points. In per-protocol analysis, the intervention effect was slightly larger but with the same pattern of a significant interaction at 6 months by IG ($\beta=0.70$, 95% CI=0.17, 1.23) compared with UCG but not at other time points

(Supplemental Table 8). In the exploratory analysis, participants in the IG who shared App data ($n=133$) had somewhat higher stroke knowledge at 6 months than the UCG ($\beta=0.86$, 95% CI=0.19, 1.53) (Supplemental Table 9).

Subgroup analysis

The intervention effect was higher in tertiary-educated, non-European, and non-Indigenous ethnic groups, and the least disadvantaged area-level SES (see Supplemental Figure 1), but not in other subgroups, including baseline LS7 category (see Supplemental Figure 2).

Stroke knowledge by domain in IG and UCG at each time point

In the main analysis, after adjusting for age, sex, education, ethnicity, SES, and country of residence in mixed-effects logistic regression models, the time by IG interaction showed that the ratio of the odds of correctly answering all stroke risk factors, but not other domains, was statistically significantly higher in IG (odds ratio (OR)=1.92, 95% CI=1.09, 3.39) compared with UCG at 3 months, but not 6 months (OR=1.73, 95% CI=0.99, 3.00) or at 12 months (OR=1.29 95% CI=0.74, 2.26) (Table 2, Figure 4). Results were consistent in the per-protocol sample (Supplemental Table 10).

Discussion

People who received the App had a small but statistically significant improvement in stroke knowledge scores compared with UCG at 6 months post-randomization, but not at 3 and 12 months. The increase in stroke knowledge from baseline to 3 months was mostly observed in the understanding of risk factors, aligned with the nature of the intervention. There was evidence of effect modification in tertiary-educated, non-European, and non-Indigenous ethnic groups, and the least disadvantaged area-level SES.

The current results support the prior pilot studies of the Stroke Riskometer™ App, which showed positive effects on stroke awareness.^{11,12} Our positive finding is supported by prior studies of other mHealth apps improving awareness and knowledge of coronary heart disease risk factors, such as the Care4Heart app,²² and other app-based interventions among individuals with diabetes²³ and hypertension.²⁴ The magnitude of the improvement in stroke knowledge in our study was small, at 0.5 units in the main analysis and 0.7 units in the per-protocol analysis on the stroke knowledge scale (range: 0–19). The clinical significance of this type of improvement in stroke knowledge on behavior change is unknown because data on the association between this stroke knowledge scale and behavior change are lacking. Although there is evidence that higher stroke knowledge predicts better health

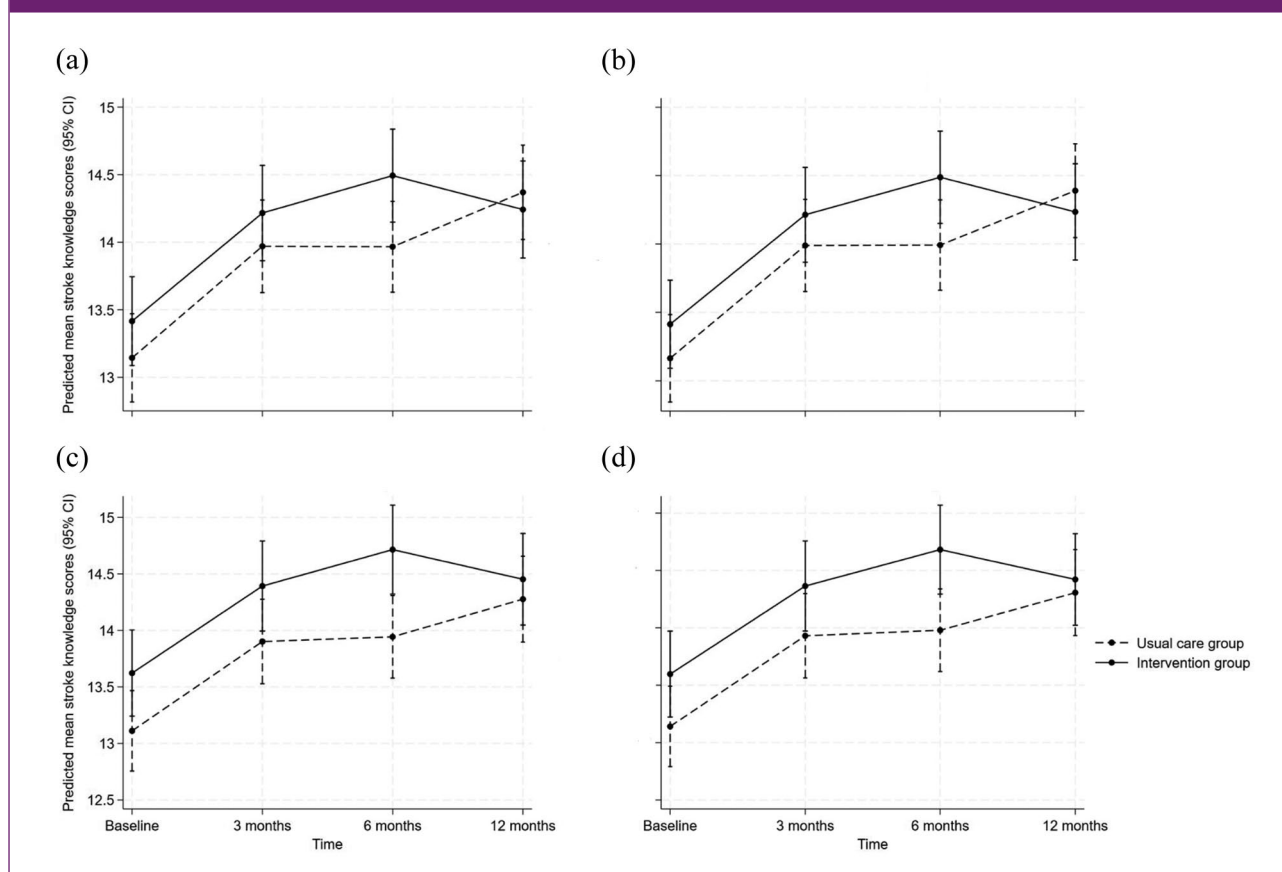
Table 1. Baseline characteristics of randomized participants.

Variables	IG (N=429)		UCG (N=433)		Total (N=862)	
	n*	%	n*	%	n*	%
Age in years						
Mean (SD)	58.1	10.7	58.2	10.9	58.1	10.8
Age groups						
35–54 years	158	36.8	158	36.5	316	36.7
55–75 years	271	63.2	275	63.5	546	63.3
Sex						
Male	154	35.9	165	38.1	319	37.0
Female	275	64.1	268	61.9	543	63.0
Level of education						
Primary and high school	159	37.1	155	35.8	314	36.4
Tertiary (university)	264	61.5	267	61.7	531	61.6
Prefer not to say	6	1.4	11	2.5	17	2.0
Ethnicity						
European	318	74.1	314	72.5	632	73.3
Indigenous	40	9.3	35	8.1	75	8.7
Non-European and non-Indigenous	71	16.6	84	19.4	155	18.0
Socioeconomic status						
Quintile 1 (most disadvantaged)	78	18.2	49	11.3	127	14.7
Quintile 2	55	12.8	67	15.5	122	14.2
Quintile 3	93	21.7	87	20.1	180	20.9
Quintile 4	109	25.4	123	28.4	232	26.9
Quintile 5 (least disadvantaged)	94	21.9	107	24.7	201	23.3
Country						
Australia	212	49.4	212	49.0	424	49.2
New Zealand	217	50.6	221	51.0	438	50.8
Stroke knowledge score						
Mean (SD)	13.4	3.6	13.2	3.6	13.3	3.6
Baseline LS7 category						
Low	110	25.7	90	20.8	200	23.2
Intermediate	155	36.1	149	34.4	304	35.3
High	164	38.2	194	44.8	358	41.5

IG, intervention group; UCG, usual care group; SD, standard deviation; LS7, Life's Simple 7.

*n (%) unless otherwise indicated.

Figure 3. Predictive margins plot. Main analysis sample: (a) Unadjusted, (b) adjusted, and for the per-protocol analysis sample, (c) unadjusted and (d) adjusted. Adjusted models include age, sex, level of education, ethnicity, SES, and country of residence.



behaviors, potentially moderated by individual context, such as stroke risk.²⁵

While knowledge initially increased in the IG, a modest reduction in stroke knowledge over time was observed, consistent with the findings of a prior mHealth study.²² The difference between the IG and UCG at 12 months was small and mostly due to an increase in knowledge in the UCG rather than a loss of knowledge in the IG. Public awareness campaigns that mostly focused on the Face-Arm-Speech-Time (FAST) message ran in both Australia and New Zealand during our trial, which may have increased knowledge among the general population. This aligns with the largest increase in the proportion of people getting all the questions correct for the UCG, which was for stroke management, which is covered in FAST. Looking at within-group differences in knowledge, the mean stroke knowledge scores in the App users consistently increased from baseline to 6 months, but slightly declined at 12 months. This suggests that while the App was impactful, its effect may not be sustained over the long-term. This may be explained by the decay effect theory, where information fades over time unless maintained via rehearsal or reactivation, which is common after

health educational interventions.²⁶ It is common for people to use the mHealth apps initially and then taper off. For example, in a physical activity intervention using the Carrot app (mHealth app with gamification to enhance use), over 60% engaged with the app for more than 6 months, but only 29% continued using it for 12 months.²⁷ From this, we can infer that mHealth app-based interventions are effective in the short term; however, strategies are required for long-term maintenance of the App's effect. Since the trial, there have been further developments in the App to sustain engagement, including refined push notifications, gamification, artificial intelligence (AI) to generate tailored feedback, content updates, and an overall improved user experience. Stroke Riskometer™ App is free to users¹⁹ and, therefore, provides a cost-effective way to promote stroke knowledge compared with other stroke educational campaigns such as mass media, which require higher levels of sustained funding.²⁸

Knowledge mostly increased in relation to the understanding of stroke risk factors, aligning with the App providing a brief education on a person's risk factors, incorporating behavior-change strategies.¹⁰ Knowledge of cardiovascular disease risk factors is recognized as

Table 2. Differences in stroke knowledge in each domain in IG compared with UCG at each time point.

Domains: time × group interactions	Main analysis sample			
	Unadjusted		Adjusted*	
	OR (95% CI)	p	OR (95% CI)	p
Stroke descriptions				
UCG	Ref.		Ref.	
Baseline × IG	0.69 (0.38, 1.27)	0.235	0.70 (0.39, 1.27)	0.240
3 months × IG	1.15 (0.63, 2.09)	0.654	1.15 (0.64, 2.09)	0.636
6 months × IG	1.19 (0.66, 2.13)	0.564	1.18 (0.67, 2.11)	0.566
12 months × IG	0.94 (0.51, 1.72)	0.838	0.94 (0.51, 1.71)	0.827
Stroke warning signs				
UCG	Ref.		Ref.	
Baseline × IG	1.32 (0.79, 2.21)	0.287	1.28 (0.78, 2.11)	0.328
3 months × IG	0.84 (0.51, 1.37)	0.478	0.81 (0.50, 1.30)	0.384
6 months × IG	0.90 (0.54, 1.49)	0.685	0.88 (0.54, 1.43)	0.596
12 months × IG	0.74 (0.45, 1.22)	0.243	0.73 (0.45, 1.18)	0.201
Stroke risk factors				
UCG	Ref.		Ref.	
Baseline × IG	1.59 (0.86, 2.92)	0.137	1.58 (0.86, 2.90)	0.138
3 months × IG	1.92 (1.08, 3.40)	0.025	1.92 (1.09, 3.39)	0.025
6 months × IG	1.73 (0.99, 3.02)	0.051	1.73 (0.99, 3.00)	0.051
12 months × IG	1.30 (0.74, 2.27)	0.358	1.29 (0.74, 2.26)	0.365
Stroke management				
UCG	Ref.		Ref.	
Baseline × IG	1.65 (0.96, 2.85)	0.072	1.55 (0.91, 2.64)	0.110
3 months × IG	1.23 (0.67, 2.26)	0.514	1.16 (0.63, 2.10)	0.636
6 months × IG	1.34 (0.74, 2.41)	0.336	1.24 (0.69, 2.21)	0.467
12 months × IG	0.83 (0.44, 1.55)	0.557	0.78 (0.42, 1.44)	0.422

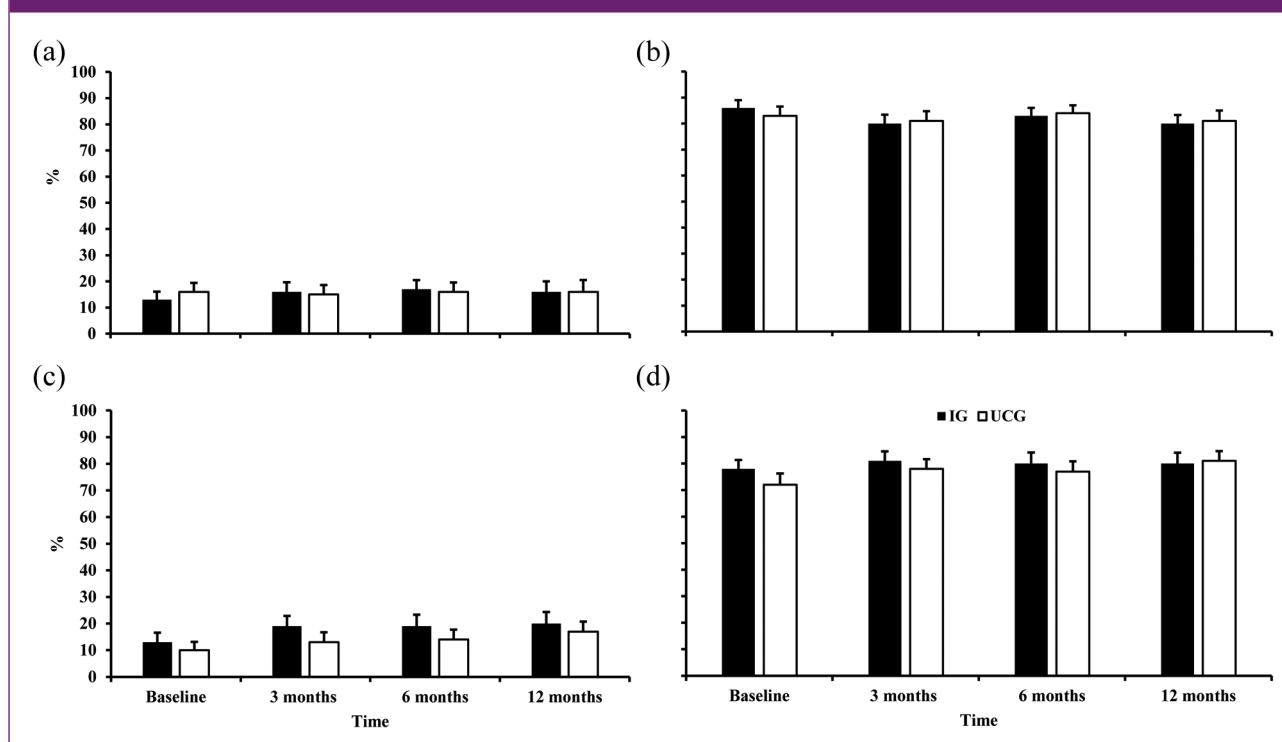
IG, intervention group; UCG, usual care group; Ref, reference category; CI, confidence interval; OR, odds ratio.

*Adjusted for age, sex, level of education, ethnicity, SES, and country of residence.

essential for health-related behavior change.²⁹ The knowledge–attitude–behavior model describes that health behaviors develop through a process of acquiring knowledge, forming attitudes, and establishing behaviors.⁶ In other studies, knowledge of coronary heart disease risk factors

was a prerequisite for the intention to engage in health-promoting behaviors.³⁰ In the primary outcome analysis of this RCT, there was no difference in the change in the LS7 score between the IG and UCG from baseline to 6 months.³¹ The current results support the notion that, over time, the

Figure 4. Proportion of people in the IG and UCG with all correct responses in stroke knowledge domains of (a) descriptions, (b) warning signs, (c) risk factors, and (d) management. IG, intervention group; UCG, usual care group.



increased stroke knowledge because of the App could translate into health behavior change. While the App is framed around stroke, the information it provides on risk factors, such as smoking or blood pressure, is relevant to the prevention of many cardiac, vascular, and other non-communicable diseases.³²

The App was more effective in tertiary-educated, non-European, and non-Indigenous ethnic groups, and the least disadvantaged area-level SES (socioeconomically most advantaged group). These differences might be attributed to underlying disparities in health or digital literacy. A previous study provided evidence that Indigenous Australians tended to have lower health literacy than non-Indigenous Australians³³ with others reporting that lower education and income levels were associated with lower health³⁴ and digital health literacy.³⁵ Health and digital literacy are important precursors to using mHealth apps.³⁶ These findings indicate that both health and digital literacy may affect the scalability of the App. Therefore, to ensure its success across diverse populations, the App could be modified to better serve individuals with lower health and digital literacy, as has been suggested for mHealth interventions targeted at secondary stroke prevention.³⁷

This study has several strengths, including that it is a multicenter international trial with a large, diverse sample and robust methodology, enhancing the validity and generalizability of the findings. The dropout rate was 6.4% at

3 months, 2.4% at 6 months, and 11.3% at 12 months, lower than previous pilot studies (16% at 6 months).¹¹ The per-protocol analysis supports the robustness of the findings by showing consistent intervention effects in the main analysis. The stronger effect in the per-protocol analysis and exploratory analysis limited to those confirmed as downloading the app suggests that fidelity of the intervention may be an issue. Only 31% of participants gave additional consent to access information on App usage. The exploratory analysis should be interpreted with caution, as it includes a subset that was particularly engaged and does not reflect randomization processes. We are planning a more detailed exploratory fidelity analysis using quantitative data on satisfaction with the app in a future analysis. A further limitation is that there is no gold standard tool for stroke knowledge;³⁸ however, we used a comprehensive, validated,²⁰ and previously used stroke knowledge tool.¹¹ We did not collect data on attitudinal change regarding stroke risk, which is also part of behavior-change processes.⁶ There was a slightly higher dropout rate in the IG at 3 months (7.9% IG vs. 4.8% UCG), 6 months (3.0% IG vs. 1.8% UCG), and 12 months (13.5% IG vs. 9.0% UCG) follow-up than UCG. Our community-based recruitment achieved a reasonably diverse participant group, acknowledging high levels of tertiary education (~60%) compared with source populations (~30%). As the effect of the App on stroke knowledge was greater in more highly educated

people, it is possible that results in the general community with fewer tertiary educated people may differ from what is shown here. There was a difference in baseline SES between the IG and UCG, although groups were well-matched on other characteristics. Some of these limitations, including the reasons for attrition, are being explored as part of a parallel quantitative and qualitative process evaluation to explore participant experiences. These findings will be reported separately and will inform App updates, potentially improving its effectiveness in changing stroke knowledge and risk factors.

Conclusion

The Stroke Riskometer™ mobile phone application resulted in a small but statistically significant improvement in stroke knowledge compared with UCG at 6 months post-randomization. However, there is overall low stroke knowledge among the general community, with few participants achieving very high scores. Future research should focus on sustaining the impact of the Stroke Riskometer™ mobile phone application on stroke knowledge and ensuring its effectiveness in people with low health or digital literacy.

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Author contributions

S.G., R.K., V.L.F., A.G.T., T.K., D.A.C., M.R.N., E.H., B.B., and D.A.B. conceived and designed the study. S.G., G.K., R.K., S.J.M., and T.K. contributed to project administration. G.K., S.J.M., and T.P. contributed to data acquisition. S.G., R.K., V.L.F., A.G.T., T.J.K., D.A.C., M.R.N., D.A.B., E.H., B.B., B.J.F., and A.D.W. contributed to methodology, while S.G., T.J.K., R.K., S.J.M., and G.K. supervised it. K.C. and A.D.W. contributed to data curation, while A.D.W., K.C., B.J.F., and D.A.B. contributed to formal analyses and interpretation. All authors contributed to drafting, revising, and approving the final version.

Declaration of conflicting interests

The authors declared the following potential conflicts of interest with respect to the research, authorship, and/or publication of this article: Valery Feigin is a shareholder and serves as Chief Scientific Adviser for PreventS-MD Ltd., a spin-off company of AUT Ventures Ltd. (Auckland University of Technology). AUT Ventures Ltd. and PreventS-MD Ltd. jointly hold the copyright for the free-to-use Stroke Riskometer app.

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Data availability statement

Data may be available on request from the corresponding author.

Supplemental material

Supplemental material for this article is available online.

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