Can personalized mobile technologies change lifestyle behaviors? A systematic review and meta-analysis

Mobile and Recommender Technology

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Ms Huong Ly Tong PhD(c) MRes BHealth

Macquarie University, University of Sydney, Australia

Twitter: @lytong22

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Disclosure

I and my spouse have no relevant relationships with commercial interests to disclose.

Learning Objectives

After participating in this session the learner should be better able to:

- Understand why personalization is important to promote behavior change
- Understand how personalized mobile technologies can be used to change lifestyle behaviors

Outline

- Background (Why we did the study)
- Methods (What we did)
- Results & Discussion (What we found)
- Conclusion (Why you should care)

Outline

- **Background**
- Methods
- Results & Discussion
- Conclusion

Background

THE ROLE OF MOBILE TECHNOLOGIES ON BEHAVIOR CHANGE

- Lifestyle behaviors can greatly influence health.
- Mobile technologies are increasingly being used to promote behavior change.
- One-size-fits-all approach doesn't work.

Outline

AMIA
INFORMATICS PROFESSIONALS. LEADING THE WAY.

Background

Methods

Results & Discussion

Conclusion

Methods

STUDY SELECTION, DATA EXTRACTION & ANALYSIS

Aims: Assess the effects of personalized mobile interventions on physical activity, diet, smoking and alcohol consumption

Databases: Medline, Embase, Scopus, PsycInfo, Cochrane library

Inclusion criteria: RCTs that tested a personalized mobile app or tracker, with a non-personalized control group, and reported a health behavior change outcome

Analysis: random-effects meta-analysis and meta-regression

Outline

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Results & Discussion

STUDY CHARACTERISTICS

13 studies

3765

48.7%

14 weeks

5 interventions

2 interventions

3 interventions

3 interventions

Results & Discussion

INTERVENTION CHARACTERISTICS

All interventions included a mobile app.

3 used trackers in conjunction.

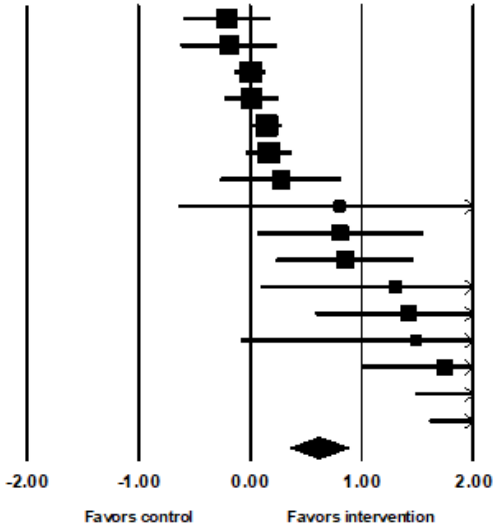
Personalized features: goal setting, feedback, behavior recommendation.

Source of data collection: 3 system-captured, 7 user-reported, 3 both.

Results & Discussion

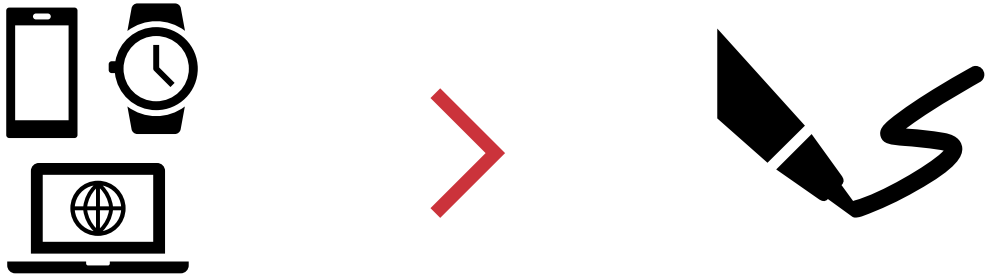
META-ANALYSIS

Study name	Std diff in means	Standard error	Variance	Lower limit	Upper limit	Z-Value	p-Value
Elbert 2016	-0.213	0.196	0.038	-0.596	0.171	-1.087	0.277
Simons 2018	-0.190	0.219	0.048	-0.619	0.239	-0.869	0.385
Recio-Rodriquez 2018	0.001	0.069	0.005	-0.134	0.137	0.021	0.983
Davies 2017	0.011	0.123	0.015	-0.231	0.252	0.089	0.929
Bertholet 2019	0.150	0.064	0.004	0.024	0.276	2.339	0.019
van Drongelen 2014	0.167	0.101	0.010	-0.032	0.366	1.647	0.100
Fanning 2017	0.276	0.276	0.076	-0.265	0.817	1.001	0.317
Rabbi 2015 II	0.802	0.735	0.540	-0.639	2.242	1.091	0.275
Fukuoka 2015 I	0.807	0.380	0.144	0.063	1.551	2.125	0.034
King 2016	0.849	0.312	0.097	0.237	1.460	2.721	0.007
Zhou 2018 II	1.303	0.612	0.375	0.103	2.503	2.129	0.033
Fukuoka 2015 II	1.417	0.423	0.179	0.588	2.245	3.351	0.001
Rabbi 2015 I	1.485	0.799	0.638	-0.080	3.050	1.859	0.063
O'Donnell 2019	1.748	0.385	0.148	0.993	2.502	4.541	0.000
Zhou 2018 I	2.093	0.311	0.097	1.483	2.704	6.722	0.000
Hochsmann 2019	2.490	0.451	0.203	1.607	3.373	5.527	0.000
	0.618	0.133	0.018	0.356	0.879	4.631	0.000



Results & Discussion

META-REGRESSION



Interventions that used system-captured data were associated with higher effectiveness than those that used user-reported data.

Results & Discussion

META-REGRESSION

Interventions that with higher retention rate were associated with higher effectiveness.

*however this effect was no longer statistically significant after adjusting for source of data collection

Outline

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Conclusion

TAKE HOME MESSAGES

Personalized mobile interventions can improve lifestyle behaviors.

Technologies that use automatic data collection seem to outperform those that use self-reported data.

@lytong22
E: huong.tong@sydney.edu.au