Latent user groups of an eHealth physical activity behaviour change intervention for people interested in reducing their cardiovascular risk

Julian Wienert a, b, Tim Kuhlmann c, Vera Storm d, Dominique Reinwand e and Sonia Lippke b, f

a Techniker Krankenkasse, Scientific Institute of TK for Benefit and Efficiency in Health Care, Hamburg, Germany; b Jacobs Center on Lifelong Learning and Institutional Development, Jacobs University Bremen, Bremen, Germany; c Department of Psychology, University of Konstanz, Konstanz, Germany; d Institute of Sports Science, University of Münster, Münster, Germany; e Department of Special Education and Rehabilitation, University of Cologne, Cologne, Germany; f Bremen International Graduate School of Social Sciences, Bremen, Germany

ABSTRACT

EHealth behaviour change interventions that help participants to adhere to professional physical activity recommendations can help to prevent future events of cardiovascular diseases (CVD). Therefore, identifying user groups of such interventions based on stages of health behaviour change is of great importance to provide tailored content to users instead of one-size-fits-all approaches. Our study used Latent Class Analysis (LCA) to identify underlying classes of users of an eHealth behaviour change intervention based on stages of change and associated variables. We compared participants’ self-allocated stage with their latent class stage membership to display the correlation and mean differences between the two approaches. This was done by analysing baseline data of N = 310 people interested in reducing their CVD risk. LCA identified a three-class solution: (non-)intenders (19.4%), non-habituated actors (43.2%) and habituated actors (37.4%). The interrelation between self-allocated and latent class stage membership was moderate (ϕ(308) = .49, p < .001). Significant mean differences for (non-)intenders and non-habituated actors were found in social-cognitive variables. Results showed that self-allocated stage outcomes represent a pseudo stage model — linear trends can be reported for stage-associated social-cognitive variables. The study provides information on the validity of stage measures, which can inform future interventions.

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Introduction

Cardiovascular diseases (CVDs) represent a major threat to health for the broader population in most countries. According to the World Health Organization (WHO) CVDs are the number one cause of death globally with an estimated 17.5 million deaths (31% of all global deaths) in 2012 (WHO, 2014). Although overall mortality rates have decreased throughout the last few years, the prevalence of CVD remains unchanged in
some countries (e.g. the United Kingdom; British Heart Foundation, 2015) and some projections for other countries, such as the US, indicate an increase by about 10% between 2010 and 2030 (Heidenreich et al., 2011). Besides medical and drug treatment, common recommendations for CVD patients strongly focus on modifiable lifestyle factors, such as physical activity, which in turn can tackle CVD risk factors such as obesity and hypertension (WHO, 2014). After initial medical CVD treatment and a post-treatment phase, usually signified by inpatient or outpatient rehabilitation, patients typically receive education on how to cope with their disease and practice new health behaviours. However, former patients often have problems complying with doctors’ recommendations when returning to their regular daily lives after surgery or rehabilitation treatment. Here, they face several problems and barriers to the implementation of newly learned health promoting behaviours (Fleury, Lee, Matteson, & Belyea, 2004; Jaarsma, Dekker, Geerzen, & Dijkstra, 2015; Zalewski, Alt, & Arvinen-Barrow, 2014). An intervention program that gives appropriate advice and support to former rehabilitation patients can be a useful tool to help to implement such behavioural strategies into daily life (Fleig, Lippke, Pomp, & Schwarzer, 2011; Fleig, Pomp, Schwarzer, & Lippke, 2013).

A promising new approach is to deliver such intervention programs via the internet as they are usually easy to implement, have a wide reach and generate few costs after their initial implementation (Bennett, & Glasgow, 2009; Webb, Joseph, Yardley, & Michie, 2010). Another advantage is that online intervention programs can easily make use of tailored content and feedback based on information provided by the user. Tailored feedback provides more specific and relevant information to the user, compared to generic “one-size-fits-all” interventions (Hawkins, Kreuter, Resnicow, Fishbein, & Dijkstra, 2008). Tailored information for individuals based on their own perceptions aims to simulate information provided in face-to-face situations (e.g. training or therapy) and thereby holds a higher relevance for the receiver (Krebs, Prochaska, & Rossi, 2010; Kreuter & Wray, 2003; Smeets, Kremers, Brug, & De Vries, 2007). Meta-analyses showed small to moderate effects of such tailored interventions for health behaviours such as physical activity (Krebs et al., 2010; Lustria et al., 2013). However, it often remains unclear who actually uses such interventions and by which means tailoring should be provided to achieve the highest possible effectiveness (Wienert & Kuhlmann, 2015).

One option to tailor health-related content in such online interventions is stages for health behaviour change (i.e. stage matching) as suggested by stage-based health behaviour change models such as the Transtheoretical Model (TTM; Prochaska et al., 2009) or the Health Action Process Approach (HAPA; Schwarzer, 2008). Stage-matched models for behaviour change assume a certain set of social-cognitive variables for each behaviour stage. This is indicated by non-linear discontinuity patterns in social-cognitive variables and their associated behavioural stage and has been studied largely referring to the TTM and HAPA (Armitage & Arden, 2002; Duan, Lippke, Wagner, & Brehm, 2011). While the TTM suggests six distinct stages: i) pre-contemplation, ii) contemplation, iii) preparation, iv) action, v) maintenance, and vi) termination, the HAPA suggests three distinct stages: i) non-intention, ii) intention, and iii) action. The HAPA stages correspond well with the TTM stages and provide a more practical and parsimonious option. The HAPA further predicts which social-cognitive variables are of importance at the different stages to influence health behaviour change, supported by stage-specific effects of these social-cognitive variables (Lippke, Ziegelmann, & Schwarzer, 2004).
Based on the assumption of stage-based behaviour change using the HAPA, **non-intenders** can be identified by having low levels of risk awareness and positive outcome expectancies, and high levels of negative outcome expectancies of a certain behaviour. An increase in risk awareness and positive outcome expectancies, and a decrease in negative outcome expectancies aim to promote the formation of behavioural intentions. **Intenders** are aware of positive and negative effects of health behaviours, however, still lack the positive experience connected to the behaviour. They are in need of preparation and planning (e.g. action plans) for the target health behaviour in order to become actors. **Actors** are well aware of the positive and negative effects of health behaviours and make use of planning strategies that help them to perform health behaviours. Actors benefit from relapse-strategies (e.g. coping plans) and self-monitoring to maintain health behaviours (Lippke, Schwarzer, Ziegelmann, Schulz, & Schüz, 2010).

Application of health behaviour change models to tailor intervention content has been studied in various contexts on – and offline, showing superior effects compared to non-matched interventions (Krebs et al., 2010; Lustria et al., 2013; Prochaska et al., 2009). Such an allocation is typically done only based on a self-allocated HAPA stage measure (i.e. subjective self-report of behavioural stages of change). Latent class analysis (LCA) allows for the allocation of participants to different unobserved groups based on categorical data which can be assessed using questionnaires. This provides the opportunity to complement tailoring of eHealth interventions based on stage measures, which might help to increase their effectiveness in the long run due to more precise tailoring of intervention content. Therefore, the current study applied a latent class approach to baseline data of study participants from a tailored eHealth intervention targeting people interested in reducing their cardiovascular risk (Kuhlmann, Reips, Wienert, & Lippke, 2016; Reinwand, Kuhlmann, Wienert, de Vries, & Lippke, 2013, Reinwand et al., 2016, Storm et al., 2016; Tan et al., 2018) and compared it to the traditional and well-validated stage measure. The theory behind stage measures assumes different patterns of social-cognitive variables between the stages (non-linear discontinuity patterns).

Our main aim was to further validate an established stage measure empirically by applying LCA. Furthermore, our study aimed at examining user groups of a tailored online intervention based on stages for health behaviour change for physical activity to identify distinct classes based on the HAPA and test the interrelation between these probability-based classes and the self-allocated behaviour stage of participants to further validate stage-measures. In order to identify underlying groups, explorative LCA was used to classify social-cognitive variables. These include risk perception, positive and negative outcome expectancies, intention, action plan, coping plans, and self-efficacy.

It was hypothesised that a three-class solution would be the best fit to the current data, identifying non-intenders, intenders, and actors on the basis of HAPA related social-cognitive variables (Hypothesis 1; Lippke et al., 2010; Parschau et al., 2012) with intenders and actors being more prominent due to the potential threat of CVD as a severe health event, which can increase intentions to adhere to physical activity recommendations and actual adherence (Hypothesis 2; Wienert, Kuhlmann, Fink, Hambrecht, & Lippke, 2017a). Separating participants into non-intenders, intenders, and actors has been shown to be a valid distinction in various health promoting behaviours, especially physical activity (Lippke et al., 2010; Parschau et al., 2012). Further, it was hypothesised
that the expected three class solution would correspond well with the self-allocation (i.e. the stage participants allocate themselves to via self-report) of participants on the basis of a health behaviour change stage measure for physical activity (Hypothesis 3), validating the stage measure as an appropriate means to tailor future online interventions on behaviour change. To the best of our knowledge this is the first study attempting to validate behavioural stages based on the HAPA by using an exploratory and advanced modelling approach.

Methods

The current study was part of a larger one, which was planned as a randomised controlled trial in Germany and the Netherlands. The cross-sectional baseline data for the present analyses from the German study arm were analysed, due to significant differences between German and Dutch study participants (Storm et al., 2016). The complete study design was published in a study protocol (Reinwand et al., 2013).

Procedure

Participants were recruited in inpatient and outpatient rehabilitation clinics by their admitted medical doctors at discharge, heart sport groups, and via a recruiting agency (Storm et al., 2016). No data on how many participants were recruited through each strategy were available. The inclusion criteria were as following: age between 20 and 85 years, no contraindications for physical activity, having an interest in improving physical activity and sufficient reading and writing skills, in addition to computer literacy and internet access. Participation in the study was voluntary and data were anonymised. All participants were informed about the study, its design and their rights as study participants before providing informed consent. The study was approved by a data protection officer and the ethics committee of the German Psychological Society (DGPs; EK-A-SL 022013) and was registered at Clinicaltrials.gov (NCT01909349). Randomization to either intervention or control group was done on the individual level and took place immediately after registration on a 1:1 ratio (i.e. one user was assigned to the intervention, the next user was assigned to the control, etc.). Both groups completed the baseline questionnaire and were analysed together.

Participants

A total of 310 German participants registered for the intervention and completed the baseline assessment. Participants were aged 23 to 80 years ($M = 52.45, SD = 12.22$), the majority (58%) was female. In total, 59% indicated living with a partner, 54% completed senior high school, 40% were working full-time, and 43% reported being moderately active for 150 min/week. Moderate activity levels are slightly above the general population in Germany (39%), but strongly exceed the overall proportion in the EU (25%; Townsend, Wickramasinghe, Williams, Bhatnagar, & Rayner, 2015).
**Measures**

HAPA based social-cognitive variables, physical activity behaviour and physical activity habit was measured online via self-report questionnaires (Reinwand et al., 2013). All scales were validated and tested for reliability in a previous study (Lippke, Wienert, Kuhlmann, Fink, & Hambrecht, 2015; Wienert, Kuhlmann, Fink, Hambrecht, & Lippke, 2016; Wienert et al., 2017a; Wienert, Kuhlmann, Fink, Hambrecht, & Lippke, 2017b).

**Risk perception**

Participants were asked to indicate their perceived level of risk of experiencing a severe CVD-related health event (e.g. heart attack) using five items asking, for example, “How likely is it that you will sometime in your life have . . .” “a high cholesterol level?”, with a 7-point Likert scale ranging from “not likely at all” to “absolutely likely” (Cronbach’s α = .87).

**Positive and negative outcome expectancies**

Participants were asked to indicate their positive and negative outcome expectancies regarding physical activity on two items each asking, for example, “If I am physically active 5 days a week for 30 minutes or more, then . . .” “I feel better afterwards” or “it will cost me a lot of time”, with a 7-point Likert scale ranging from “don’t agree at all” to “totally agree” (positive: r = .69; negative: r = .38).

**Intention**

Participants were asked to indicate their intention to perform moderate physical activity on a single item worded “On 5 days a week for 30 minutes (or a minimum of 2.5 hours per week), I have the intention to perform moderate physical activity”, with a 7-point Likert scale ranging from “don’t agree at all” to “totally agree”.

**Action plans**

Participants were asked to indicate if they already made plans to specify the situational context of their physical activity on three items asking, for example, “For the next month, I have already planned in detail which physical activities I would like to do”, with a 7-point Likert scale ranging from “don’t agree at all” to “totally agree” (Cronbach’s α = .94).

**Coping plans**

Participants were asked to indicate if they had already made plans to specify whether they have specific coping strategies that help them to overcome barriers that distract them from their physical activity on three items asking, for example, “For the next month, I have already planned in detail when I have to be especially cautious not to stop being active”, with a 7-point Likert scale ranging from “not agree at all” to “totally agree” (Cronbach’s α = .91).

**Self-efficacy**

Participants were asked to indicate if they are convinced to take up, maintain or return to their physical activity after relapse on five items, for example “I am certain that I can be physically active permanently at a minimum of 5 days a week for
30 minutes”, with a 7-point Likert scale ranging from “not agree at all” to “totally agree” (Cronbach’s $\alpha = .86$).

**Physical activity behaviour**

Physical activity behaviour was assessed using the German version of the International Physical Activity Questionnaire (IPAQ; Craig et al., 2003). The total amount of moderate physical activity in minutes per week (min/week) was calculated.

**Physical activity habit strength**

Participants were asked to indicate their habit strength regarding physical activity with an abbreviated version of the Self-Report Habit Index (SRHI; Verplanken & Orbell, 2003) on two items asking, “Being physically active for at least 30 minutes on 5 days a week is something that…” (1) “has become a confirmed habit” and (2) “I do without thinking about it”, with a 7-point Likert scale ranging from “don’t agree at all” to “totally agree” ($r = .87$).

**Stages of behaviour change for physical activity**

Stages were assessed according to a 5-point ordinal variable by Lippke and colleagues (2009, Lippke et al., 2010), which has been shown to have acceptable measurement qualities, especially when differentiating between intenders and actors. Participants were asked to indicate whether they were at least physically active 5 times a week for 30 minutes or more. The stage measure was separated according to the three HAPA stages for further analyses: non-intender, intender, actor. Non-intenders were classified via “No, and I do not intend to start” (1), intenders via “No, but I am considering it” and “No, but I seriously intend to start” (2), and actors via “Yes, but I find it rather difficult” and “Yes, and I find it rather easy” (3). An ordered categorical stage measure with five options was chosen to allow for adjustments if necessary after applying exploratory latent class analysis (i.e. expected classes cannot be identified via latent class analysis). Stages of the HAPA were operationalised to assess stage allocation for physical activity as the target behaviour.

**Statistical analyses**

Analyses were conducted using SPSS 22.0 and Mplus 7.3. Hypothesis 1 and Hypothesis 2 were tested using LCA starting with the hypothesised three-class variant and testing a two class and a four-class solution afterwards to compare relative fit indices and to evaluate the quality of the three-class solution. Latent class models include one or more discrete unobserved variables and provide a powerful tool to structure data by using probability-based classifications, as they do not rely on traditional model assumptions (e.g. linear relationship; Magidson, & Vermunt, 2002). The model assigns each individual a probability of class membership to account for uncertainty in class membership. Each identified class is characterised by its estimated prevalence and the probability of individuals within that class exhibiting each observed variable.

LCA can only interpret dichotomous variables, following the assumption that the probability of a case’s response depends on the latent class he or she belongs to (von Eye, Bergman, & Hsieh, 2015). Additionally, LCA lets the variables follow any distribution,
as long as they are unrelated to each other (independent) within classes (Oberski, 2016). Seven-point Likert scales (all but IPAQ and stage for behaviour change) were split at 3.5 to separate each scale into low (0) and high (1) values. The IPAQ cut-off was chosen at 150 min/week (Sattelmair, Pertman, Ding, Kohl, & Haskell et al., 2011), representing insufficient moderate physical activity levels (0) and sufficient physical activity levels (1). Entropy, Vuong-Lo-Mendell-Rubin Likelihood Ratio Test, Lo-Mendell-Rubin Adjusted likelihood ratio test as well as Akaike Information Criterion (AIC), Bayesian Information Criterion (BIC) and sample size adjusted BIC were used to evaluate the model fit.

Conducting LCA, Mplus 7.3 assigned a number corresponding to the membership of each case to one of the classes. The data were then re-imported into SPSS 22.0 with the new defined variable and matched on basis of their study ID. Hypothesis 3 was tested using the Spearman’s rho (ρ) to test the interrelationship between the two ordered ranks. In the next step, means were calculated for all variables on basis of the three HAPA stages and the identified latent classes to analyse mean differences and linear and quadric trends using analysis of variance (ANOVA) to identify stage specific trend patterns using polynomial contrast to test for non-linear trends and weighted terms to account for differences in group size. Linear trends would only support a pseudo stage model while quadric trends support discontinuity in variables between stages, following the assumption that social-cognitive variables that influence the probability of moving to the next stage should differ depending on the current stage a person is in (Armitage & Arden, 2002; Sutton, 2000). Differences between self-allocated and latent stage outcomes on all included social-cognitive variables, significant at p < .05, are highlighted as subsequent effect sizes were reported using Cohen’s d (small effect: d ≥ 0.2, medium effect: d ≥ 0.5, large effect: d ≥ 0.8; Cohen, 1992).

**Results**

**Latent classes**

The latent class model using three classes had a fair fit looking at Entropy as a first indicator to evaluate the models’ quality. AIC and sample adjusted BIC suggested that a solution with three classes would be appropriate. Lo-Mendell-Rubin Adjusted LRT Test suggested that a solution with two classes performed significantly better than a single class solution and a solution with three classes performed significantly better than two classes (Table 1). Though a solution with four classes had higher Entropy, increases in AIC, BIC and sample size adjusted BIC pointed towards a solution with two classes or three classes. This was further supported by the Lo-Mendell-Rubin Adjusted LRT Test. Carefully assessing the different criteria it was decided to further analyse the model with the three-class solution. This model led to three interpretable classes which differed from the expected classification of (non-)intenders, intenders, and actors and were labelled (non-) intenders, non-habituated actors and habituated actors (Table 2). The results of the three class solution are displayed in Figure 1.

**Class 1 – (Non-)Intenders (19.4%):** had high probabilities for positive and negative outcome expectancies and medium probabilities for risk perception, intention, self-efficacy and physical activity behaviour. Class 1 had low probabilities for action plans and coping plans, as well as physical activity habit. Probabilities suggest that this class can be described by members with medium risk perception, but also with high positive

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and negative outcome expectancies, which might result in uncertainty regarding physical activity outcomes. Additionally, there is a medium probability for high intentions to engage in physical activity, as well as performing a sufficient amount of physical activity.

Table 1. Criteria for assessing fit for different number of classes.

|                | 2 Classes | 3 Classes | 4 Classes |
|----------------|-----------|-----------|-----------|
| AIC            | 2934      | 2912      | 2915      |
| BIC            | 3005      | 3020      | 3061      |
| Sample size adjusted BIC | 2945      | 2928      | 2937      |
| Entropy        | .699      | .736      | .892      |
| Lo, Mendell, Rubin Adjusted LRT Test | 2 v 1 | 3 v 2 | 4 v 3 |
| Value          | 177       | 41        | 17        |
| $p < .001$     | $p = .012$ | $p = .048$ |           |
| $N$ for each class | C1 = 109 | C1 = 60 | C1 = 59 |
|                | C2 = 201  | C2 = 134  | C2 = 102  |
|                | C3 = 116  | C3 = 60   | C3 = 60   |
|                | C4 = 89   |           |           |

Table 2. Probabilities for the three-class solution to have a high value ($= 1$) on the designated indicator.

| Overall proportion | First class label (Non-)Intenders | Second class label Non-habituated actors | Third class label Habituated actors |
|--------------------|-----------------------------------|-----------------------------------------|-----------------------------------|
| Risk perception    | .44                               | .42                                     | .54                               |
| Positive outcome expectancies | .96   | .88                                     | .99                               |
| Negative outcome expectancies | .41       | .71                                     | .34                               |
| Intention          | .76                               | .50                                     | .82                               |
| Action plans       | .82                               | .26                                     | .92                               |
| Coping plans       | .53                               | .01                                     | .50                               |
| Self-efficacy      | .81                               | .48                                     | .87                               |
| Physical activity behaviour | .68   | .51                                     | .64                               |
| Physical activity habit strength | .44   | .14                                     | .15                               |
| $N$                | 310                               | 60                                      | 134                               |
| 116                |                                     |                                         |                                   |

Figure 1. Answer probabilities for the three-class solution.
(i.e. 150 min/week of moderate physical activity). Low probabilities for action and coping plans, which are exclusive volitional strategies to transit from the intentional to the action stage (Schwarzer, 2008), as well as a low probability for physical activity habit, led to the interpretation of this class being defined as (non-)intenders (Table 2).

**Class 2 – Non-habituated actors (43.2%):** had the highest probabilities for risk perception and positive outcome expectancies and high probabilities for intention, action plans and self-efficacy. Medium probabilities can be reported for coping plans and physical activity behaviour, whilst low probabilities can be reported for physical activity habit strength. Compared to Class 1, Class 2 had higher probabilities for risk perception and positive outcome expectancies, but lower probabilities for negative outcome expectancies. Higher probabilities for intention, action plans, coping plans, self-efficacy and physical activity behaviour can be reported. This suggests that members of this class already advanced further in the health behaviour change process by identifying a higher need to perform physical activity based on their higher risk perception, but probably also had positive experiences with physical activity based on higher probabilities for positive and lower probabilities for negative outcome expectancies. Members of this class are very likely to already apply action plans to structure their time and pursue physical activity subsequently. However, the medium probability for coping plans to overcome daily barriers might help to explain the medium probability shown for physical activity behaviour, though the behaviour was shown more frequently than in Class 1. Due to the high probability for intention and action plans, the medium probability for coping plans and physical activity and a low probability for physical activity habit strength, this class might be described as non-habituated actors (Table 2).

**Class 3 – Habituated actors (37.4%):** had the highest probability for intention, action plans, coping plans, self-efficacy, physical activity behaviour and physical activity habit strength. Additionally, this class can be described as having the lowest probability for high risk perception and negative outcome expectancies. Compared to the other classes, this class showed features to be located at the very end of the health behaviour change process due to the high probability for physical activity habit. Hence, this group might be adequately described as habituated actors (Table 2).

**Social-cognitive variables associated with latent classes**

As described above, data were re-imported into SPSS based on the three-class solution to report Spearman’s rho (ρ). The results of the latent class analysis suggest that the expected stage separation (non-intender, intender, and actor) would not fit the data appropriately. Therefore, the separation of the stage measure was re-classified accordingly. (Non-)Intenders were classified via “No, and I do not intend to start”, “No, but I am considering it” and “No, but I seriously intend to start” (1), non-habituated actors via “Yes, but I find it rather difficult” (2), and habituated actors via “Yes, and I find it rather easy” (3). Distribution of self-allocated answers on the ordered categorical stage algorithm and the three stages derived from the recoding into (non-)intenders, non-habituated actors, and habituated actors are displayed in Table 3.

Distribution between self-allocation to HAPA stages and latent class classification (LCA stages) varied strongly. While 55.5% were allocated to being (non-)intenders (n = 172), 22.3% were allocated to being non-habituated actors (n = 69), and 22.3% allocated habituated actors (n = 69). Based on the latent class analysis 19.4% were (non-) intenders (n = 60), 43.2% were non-habituated actors (n = 134), and 37.4% were
habituated actors \((n = 116)\). There was a moderate relationship between self-allocation to HAPA stages and the classification via latent class analysis \(\rho(308) = .49, p < .001\).

**Differences between latent class analysis stages and self-allocated HAPA stages**

After analysing differences in means between LCA stages and self-allocated HAPA stages, significant differences can be reported for positive outcome expectancies, negative outcome expectancies, intention, action plans, coping plans and physical activity habit strength in (non-)intenders, and for coping plans and physical activity habit in non-habituated actors (Table 4). Effect sizes reporting Cohen’s \(d\) ranged from \(d = 0.42\) (small effect) to \(d = 1.10\) (large effect). There were no significant differences between habituated actors. Both analyses showed similar results on the mean level; however, smaller standard deviations for LCA stages suggested equal or less spread in data values for most scales in 79% of variables under investigation. Furthermore, the results show that only (non-)intenders fail to achieve the recommended amount of 150 min/week of moderate physical activity behaviour when referring to self-allocated HAPA stages whereas (non-)intenders as well as non-habituated actors fail to achieve the recommended amount of time when referring to LCA stages. Taking a closer look at the means of physical activity behaviour across LCA stages, there was no significant mean difference between (non-)intenders \((M = 133.00, SD = 276.50)\) and non-habituated actors \((M = 139.22, SD = 245.48)\); \(t(192) = 0.16, p = 0.88\). However, significant mean differences can be reported between (non-)intenders \((M = 133.00, SD = 276.50)\) and habituated actors \((M = 261.47, SD = 363.00)\); \(t(174) = 2.40, p = 0.02\) as well as non-habituated actors \((M = 139.22, SD = 245.48)\) and habituated actors \((M = 261.47, SD = 363.00)\); \(t(248) = 3.15, p = 0.002\) regarding physical activity behaviour.

The results show that the HAPA stages might not sufficiently differentiate between stages regarding risk perception, as well as positive and negative outcome expectations as indicated by relatively equal means across stages, whilst this only holds true for risk perception in the LCA stages. Furthermore, investigating linear and quadratic terms, our results emphasize that the classification based on manifest HAPA stages implies pseudo stages whilst only the LCA stages supported discontinuity patterns for positive outcome expectancies, negative outcome expectancies, intention, action plans and physical activity habit strength. Hence, only the LCA stages showed features of a “true stage” model in this study.

### Table 3. Cross-tabulation of stages based on LCA and stages according to the new recoding of health behaviour stages on basis of LCA.

| Classification based on artificial recode | (Non-)Intenders | Non-habituated actors | Habituated actors |
|-----------------------------------------|----------------|----------------------|------------------|
| (Non-)Intenders                         | 52             | 88                   | 32               |
| Non-habituated actors                   | 5              | 33                   | 31               |
| Habituated actors                       | 3              | 13                   | 53               |
| N                                       | 60             | 134                  | 116              |
Table 4. Means, standard deviations, linear trends, quadric trends, significance levels and absolute effect size Cohen’s $d$ derived from analysis of variance for intenders, non-habituated actors and habituated actors for self-allocated HAPA stages and classification based on latent class analysis.

|                      | HAPA stages |                      | LCA stages |                      |                      |                      |                      |                      |
|----------------------|-------------|----------------------|------------|----------------------|----------------------|----------------------|----------------------|----------------------|
|                      | 1 (Non-)    | 2                    | 3          | Linear term, $F$     | 1 (Non-)             | 2                    | 3          | Linear term, $F$     |                      |
|                      | Intenders   | Non-habituated      | Habituated | Quadric term, $F$   | Intenders             | Non-habituated      | Habituated | Quadric term, $F$   |                      |
|                      | $n = 172$   | actors $n = 69$      | actors $n = 69$ |                      | $n = 60$             | actors $n = 134$      | actors $n = 116$ |                      |                      |
| Risk perception      | 3.37 (1.34) | 3.31 (1.37)          | 3.16 (1.22) | 1.12                 | 3.31 (1.35)          | 3.51 (1.35)          | 3.10 (1.26) | 2.03                 | 3.87                 |
|                      |             |                      |             | 0.05                 |                      |                      |             |                      |                      |
| Positive outcome     | 6.30 (1.14) | 6.19 (1.26)          | 6.25 (1.33) | 0.19                 | 5.69 (1.66)          | 6.44 (0.74)          | 6.37 (1.28) | 9.43***              | 8.56**               |
| expectancies         |             |                      |             | 0.24                 |                      |                      |             |                      |                      |
| Negative outcome     | 3.31 (1.43) | 3.34 (1.61)          | 2.83 (1.51) | 3.81                 | 4.10 (1.25)          | 3.06 (1.44)          | 2.91 (1.50) | 22.62***             | 6.75*                |
| expectancies         |             |                      |             | 1.71                 |                      |                      |             |                      |                      |
| Intention            | 4.28 (1.27) | 4.44 (1.47)          | 4.81 (1.32) | 6.80***              | 3.61 (1.27)          | 4.50 (1.16)          | 4.79 (1.39) | 29.97***             | 4.08*                |
|                      |             |                      |             | 0.35                 |                      |                      |             |                      |                      |
| Action plans         | 4.61 (1.86) | 5.59 (1.41)          | 5.84 (1.40) | 31.41***             | 2.69 (1.61)          | 5.28 (1.32)          | 6.14 (0.88) | 272.80***            | 35.05***             |
|                      |             |                      |             | 2.49                 |                      |                      |             |                      |                      |
| Coping plans         | 3.05 (1.63) | 4.07 (1.66)          | 4.70 (1.84) | 51.65***             | 1.87 (0.80)          | 3.23 (1.51)          | 5.02 (1.47) | 220.60***            | 1.72                 |
|                      |             |                      |             | 0.67                 |                      |                      |             |                      |                      |
| Self-efficacy        | 4.56 (1.41) | 5.00 (1.21)          | 5.07 (1.42) | 8.40**               | 3.61 (1.35)          | 4.86 (1.20)          | 5.26 (1.26) | 61.21***             | 8.37**               |
|                      |             |                      |             | 0.86                 |                      |                      |             |                      |                      |
| Physical activity    | 114.33      | 171.16               | 369.42     | 59.91***             | 133.00               | 139.22               | 261.47      | 9.80**               | 2.80                 |
| behaviour            | (229.12)    | (260.96)             | (419.84)   |                      | (276.90)             | (245.48)             | (363.00)    |                      |                      |
| Physical activity    | 2.49 (1.60) | 3.77 (1.55)          | 5.23 (1.66) | 148.20***            | 1.81 (1.08)          | 2.28 (1.12)          | 5.44 (1.09) | 552.10***            | 106.49***            |
| habit                |             |                      |             | 0.17                 |                      |                      |             |                      |                      |

Notes: *$p < .05$; **$p < .01$; ***$p < .001$; 11 significance level for difference between intenders in HAPA stages and LCA stages; 22 significance level for difference between non-habituated actors in HAPA stages and LCA stages; absolute values are reported for Cohen’s $d$. 
Discussion

By using latent class analysis, three classes of intervention users were identified based on the HAPA: (non-)intenders, non-habituated actors, and habituated actors. To our knowledge, this is the first study to use such an approach to determine user groups of an online intervention to promote a healthy lifestyle and to validate self-allocation on behavioural stages.

Partly confirming Hypothesis 1, three classes could be identified using latent class analysis; however, these could not be classified as non-intender, intender, and actor. Interpreting the three classes it seems more likely that a class of (non-)intenders can be described, as well as non-habituated actors and habituated actors. (Non-)Intenders can be described by higher probabilities for high positive and negative outcome expectancies, as well as medium probabilities for high intentions and self-efficacy, and sufficient moderate physical activity. Interpreting the probabilities, it seems that class members are well aware of pros but also identify cons of sufficient physical activity, maybe because they lack self-regulatory strategies that help them translate good intentions into behaviour in the long run. However, this class partly realizes sufficient levels of physical activity. Non-habituated actors can be described by higher probabilities for having high positive outcome expectancies, intentions and self-efficacy and by making use of action plans. Members of this class are mainly aware of beneficial effects of physical activity possibly due to a higher self-efficacy, which might have been achieved by mastery experience and the adoption of action plans to initially start physical activity. Habituated actors can be described by higher probabilities in nearly all HAPA constructs that facilitate health behaviour change, except risk perception. Members of this class additionally also have a higher probability for higher levels of coping planning and self-efficacy besides sufficient physical activity level and the habituation of physical activity on a sufficient level, probably due to the application of coping plans.

Due to the identified stages using exploratory LCA and based on the interpretation of probabilities, the results are in line with Hypothesis 2, as non-habituated actors and habituated actors make up for 81% of the total sample, while only 44% allocate themselves into one of the actor categories. This gap between latent class membership and self-allocation is also reflected by a moderate correlation between the two, partly supporting Hypothesis 3 after adjusting HAPA stages for self-allocation based on results from the latent class analysis. Displaying the distribution of (non-)intenders, non-habituated actors and habituated actors revealed a rather large discrepancy between LCA-based identification and self-allocation of (non-)intenders. This might indicate that some persons assigning themselves to “No, and I do not intend to start”, “No, but I am considering it” and “No, but I seriously intend to start” might underestimate their current stage, though they might be located further along in the health behaviour change process.

Further analysing differences in HAPA constructs between latent class membership and self-allocation, it is not surprising that (non-)intenders in both conditions differed the most, indicating a poor overlap between class membership and self-allocation. This is also reflected by mainly medium to large effect sizes reporting Cohen’s $d$ (i.e. $d = 1.10$ for action plans). Smaller standard deviations for most variables in self-allocated HAPA stages point towards a slightly more heterogeneous sub-sample in the latent class approach,
especially for non-habituated actors. Interpreting linear and cubic trends, the HAPA stages show properties of a pseudo stage model, while only the LCA stages display discontinuity patterns. These patterns are present for positive outcome expectancies, negative outcome expectancies, intention, action plans and physical activity habit strength. It is also worthwhile to mention that only habituated actors in the LCA stages classification met physical activity recommendations, while this can be reported for non-habituated actors and habituated actors in the self-allocated HAPA stage classification.

Hence, results from the two-sample t-test analysing mean differences between LCA stages and self-allocated stages should be interpreted with caution due to the artificial, post-hoc recoding of stages prior to analysis (i.e. recoding of the answers to the stage measure into (non-)intenders, non-habituated actor, and habituated actors). Due to this recoding, our study lacks the clear distinction between non-intenders and intenders. Furthermore, the HAPA was used as a theoretical framework to analyse and interpret our data, which mainly focuses on three stages: non-intender, intender, and actor. However, results from the probability distribution of social-cognitive variables indicate that these would likely mirror theoretical descriptions of the preparation, action, and maintenance stages of the TTM by Prochaska et al. (2009) more accurately.

Despite identifying three classes, the overlap between LCA classes and self-allocated stages can only be described as medium at best – probably because of the artificial recoding of HAPA stages or the implemented stage measure, which might lack sensitivity to sufficiently discriminate between stages. A theoretical lack of discrimination between non-habituated actors and habituated actors using the HAPA is rather unlikely due to the included action control after behaviour realization (Schwarzer, 2008). Nevertheless, the current results identified that three different classes of persons used the intervention in a slightly more precise way as indicated by smaller or equal standard deviations in 79% of variables and by providing better distinct stages as indicated by discontinuity patterns. Following LCA classification, (non-)intenders might underestimate themselves when self-indicating their stage allocation. This might point towards a problem in participants’ self-awareness when answering questions on social-cognitive predictors for physical activity and the stage measure for physical activity. Additionally, the current study had a large scope by addressing persons interested in reducing their cardiovascular risk which included persons who completed inpatient or outpatient rehabilitation, participated in heart sport groups or were recruited using the panel of a recruiting agency. Future studies should therefore target a more specific population (e.g. completed inpatient rehabilitation), to provide more specific information on user groups of an eHealth intervention (e.g. type of CVD event, time since event, severity) and that also addresses a specific type of training and exercise (e.g. high-velocity resistance exercise when high-intensity resistance exercise is contraindicated; Miyamoto, Kamada, & Moritani, 2017). Furthermore, the current study only addressed physical activity as a single behaviour to classify intervention users. Future studies might also benefit from a multiple health behaviour change perspective that addresses cross-behavioural mechanisms when identifying latent user groups (Paech & Lippke, 2017).

**Conclusion**

Our study identified three distinct user groups of an eHealth intervention for persons interested in reducing their cardiovascular risk. Based on a latent class approach, the three
distinct classes of (non-)intenders, non-habituated actors, and habituated actors were identified and showed a moderate interrelationship between the probability-based classes and self-allocation of participants on a stage measure. The study sheds more light on the validity of stage measures, which might be used as a basis for tailoring health promotion interventions delivered through the internet. Furthermore, the results imply that intervention users of the current study were mainly active or were already intending to be so as our current latent class solution with three classes failed to identify a class that could be labelled as non-intenders. It might be possible that a solution with more classes might have been able to identify such a group, but there is also a chance that the results raise the question for effective recruiting strategies to reach persons who are not sufficiently active (i.e. non-intenders) and thereby might increase their risk for CVD.

Our results are valuable for future research and for practice that makes use of stage-based measures of health behaviour change for tailoring physical activity promoting interventions towards participants by highlighting a potential lack of discrimination between non-habituated actors and habituated actors using the tested stage measure. Further investigating the predictive differences between self-allocation and probability-based allocation of stages for the effectiveness of interventions is also a possible venue for future studies.

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ORCID

Julian Wienert http://orcid.org/0000-0003-1246-7591
Tim Kuhlmann http://orcid.org/0000-0003-4673-1733
Vera Storm http://orcid.org/0000-0002-7106-1738
Dominique Reinwand http://orcid.org/0000-0002-1567-1005
Sonia Lippke http://orcid.org/0000-0002-8272-0399

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