Subtypes of smokers in a randomized controlled trial of a web-based smoking cessation program and their role in predicting intervention non-usage attrition: Implications for the development of tailored interventions

Si Wen [a,*], Reinout W. Wiers [a,b], Marilisa Boffo [a,c], Raoul P.P.P. Grasman [d], Thomas Pronk [a,e], Helle Larsen [a]

[a] Addiction Development and Psychopathology (ADAPT)-lab, Department of Psychology, University of Amsterdam, Amsterdam, the Netherlands
[b] Center for Urban Mental Health, University of Amsterdam, Amsterdam, the Netherlands
[c] Department of Psychology, Education and Child Studies, Erasmus University Rotterdam, Rotterdam, the Netherlands
[d] Programme group Psychological Methods, Department of Psychology, University of Amsterdam, Amsterdam, the Netherlands
[e] Open Science Tools (PsychoPy)-Lab, School of Psychology, University of Nottingham, Nottingham, United Kingdom of Great Britain and Northern Ireland

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ABSTRACT

Introduction: Web-based smoking interventions hold potential for smoking cessation; however, many of them report low intervention usage (i.e., high levels of non-usage attrition). One strategy to counter this issue is to tailor such interventions to user subtypes if these can be identified and related to non-usage attrition outcomes. The aim of this study was two-fold: (1) to identify and describe a smoker typology in participants of a web-based smoking cessation program and (2) to explore subtypes of smokers who are at a higher risk for non-usage attrition (i.e., early dropout times).

Methods: We conducted secondary analyses of data from a large randomized controlled trial (RCT) that investigated effects of a web-based Cognitive Bias Modification intervention in adult smokers. First, we conducted a two-step cluster analysis to identify subtypes of smokers based on participants' baseline characteristics (including demographics, psychological and smoking-related variables, $N = 749$). Next, we conducted a discrete-time survival analysis to investigate the predictive value of the subtypes on time until dropout.

Results: We found three distinct clusters of smokers: Cluster 1 (25.2%, $n = 189$) was characterized by participants being relatively young, highly educated, unmarried, light-to-moderate smokers, poly-substance users, and relatively high scores on sensation seeking and impulsivity; Cluster 2 (41.0%, $n = 307$) was characterized by participants being older, with a relatively high socio-economic status (SES), moderate-to-heavy smokers and regular drinkers; Cluster 3 (33.8%, $n = 253$) contained mostly females of older age, and participants were further characterized by a relatively low SES, heavy smoking, and relatively high scores on hopelessness, anxiety sensitivity, impulsivity, depression, and alcohol use. Additionally, Cluster 1 was more likely to drop out at the early stage of the intervention compared to Cluster 2 (adjusted Hazard Ratio ($HR_{adjusted}$) = 1.51, 95% CI = [1.25, 1.83]) and Cluster 3 ($HR_{adjusted}$ = 1.52, 95% CI = [1.25, 1.86]).

Conclusions: We identified three clusters of smokers that differed on a broad range of characteristics and on intervention non-usage attrition patterns. This highlights the heterogeneity of participants in a web-based smoking cessation program. Also, it supports the idea that such interventions could be tailored to these subtypes to prevent non-usage attrition. The subtypes of smokers identified in this study need to be replicated in the field of e-health outside the context of RCT; based on the smoker subtypes identified in this study, we provided suggestions for developing tailored web-based smoking cessation intervention programs in future research.

* Corresponding author at: Addiction Development and Psychopathology (ADAPT)-Lab, Department of Psychology, University of Amsterdam, Postbus 15916, 1001 NK Amsterdam, the Netherlands.
  E-mail addresses: si-wen@hotmail.com, s.wen@uva.nl (S. Wen).

1. Introduction

Web-based smoking interventions offer the promise of efficiently delivering smoking cessation programs and services to a large number of individuals (Abrams et al., 2010). However, the main challenge of web-based smoking cessation interventions is to engage people or keep people engaged in an intervention. For example, in many web-based smoking cessation interventions, a substantial proportion of participants never use the intervention or stop with it early, resulting in low usage rates (Cantrell et al., 2016; Saul et al., 2016; Wangberg et al., 2008). In a landmark paper published in 2005, Eysenbach has defined these phenomena as "non-usage attrition" (also known as low levels of adherence and engagement) and has argued for a "science of attrition" in the field of eHealth research (Eysenbach, 2005). Although greater intervention usage does not automatically mean greater intervention effectiveness, a dose-response relationship for the use of web-based smoking cessation interventions has been found with higher levels of usage being related to better smoking outcomes (see Hutton et al., 2011 for a review). Therefore, the non-usage attrition issue needs to be further examined in order to improve the uptake and continuation, and thus the impact of web-based smoking cessation interventions.

One of the explanations for non-usage attrition in web-based intervention programs is that the intervention may not always meet participants' personal needs and preferences. For example, a recent review of web-based interventions has shown that negative perceptions of intervention formats and contents were often cited as reasons for high levels of non-usage attrition (Beatty and Binnion, 2016). Similar results have been found in the smoking domain. For example, in a study that investigated the reasons why participants dropped early out from BecomeAnEX.org (a popular Cognitive Behavior Therapy (CBT) websites for smoking cessation), among 282 respondents for the investigation, 24% indicated that "the intervention did not have the intervention elements or the resources (e.g., free medicine) I was looking for", 7% indicated that "some intervention elements were not comfortable for me", and 7% indicated that "the intervention was hard to use" (Saul et al., 2016). Given these results and the theoretical perspective of user-centered intervention design approaches (van Gemert-Pijnen et al., 2018), the non-usage attrition issue may be countered by tailoring the intervention programs to the needs of different users. This perspective has yielded interest in developing varieties of approaches for intervention tailoring, one of which is to identify typologies of intervention users to tailor intervention according to their characteristics (e.g., Batra et al., 2008; del Río et al., 2011). The basic idea of identifying typologies of intervention users is that the specific needs of intervention users can be better served if an intervention program is developed to match their characteristics. In turn, this can lead to improved intervention outcomes, including better levels of adherence and engagement. Following this idea, in order to reduce non-usage attrition rates in web-based smoking interventions, investigating subtypes of smokers who participate in such interventions is an important first step.

Previous studies have identified smoker typologies in general smokers who did not seek help to quit smoking (e.g., Cohn et al., 2017; Furberg et al., 2005; Manley et al., 2009; Timberlake, 2008) and in smokers who participated in studies on face-to-face smoking interventions (e.g., Batra et al., 2008; del Río et al., 2011). In these previous studies, some commonly assessed variables in smoking research or some pre-treatment characteristics have been used to investigate smoker typologies, such as demographics, smoking-related motives, behaviors, and complications, alcohol and other substance use, personality factors, and variables related to smoking cessation, etc.; results of these studies suggest that smokers are a very heterogeneous population that differed on these variables. However, to the best of our knowledge, no studies have investigated smoker typologies in web-based smoking interventions based on a larger number of pre-treatment characteristics. Additionally, although a large number of variables have differentiated smokers in these previous studies, individual studies have focused on a single variable or only a few (see summaries in del Río et al., 2011; Furberg et al., 2005). To better inform tailoring of web-based smoking cessation interventions, it is important to gain a comprehensive understanding of the heterogeneity of smokers participating in web-based smoking cessation interventions. Thus, we aimed to achieve this by including a wide range of variables that have differentiated smokers in these previous studies. Clustering-based techniques involve identifying individuals who score similarly on a large set of variables and grouping individuals with nearly identical profiles into a distinct subtype (Laursen and Hoff, 2006). This approach has the capability to uncover multi-dimensional smoker profiles, which could provide intervention designers with a more holistic impression of smoker typologies and with multiple targets for profile-tailored interventions, and could also guide the formation of basic focus groups to help intervention designers develop tailored interventions.

Apart from the descriptive purpose, typologies are also used because of their ability to predict prospective behaviors such as intervention outcomes and attrition (e.g., Batra et al., 2008). Investigating the predictive ability of user subtypes on non-usage attrition could help uncover subtypes that are at a higher risk of attrition. Intervention developers may need to pay extra attention to those subtypes when designing future interventions. However, this line of research is still in its infancy in the field of web-based smoking cessation interventions (c. f., Beatty and Binnion, 2016). Only few studies have investigated pre-treatment characteristics as predictors of non-usage attrition in web-based smoking cessation interventions, and they have mainly focused on demographics and smoking-related variables (Balmford et al., 2008; Bricker et al., 2018b; Cantrell et al., 2016; Graham et al., 2006; Perski et al., 2021; Strecher et al., 2008; Wangberg et al., 2008). These studies showed that smokers who are younger, male, less educated, less addicted to tobacco, less ready to change, and do not receive other smoking cessation aids (e.g., e-cigarettes or pharmacotherapy) are more likely to stop using web-based smoking cessation interventions. Additionally, we know that several psychological factors such as substance use-related personality factors of sensation seeking, impulsivity, hopelessness, and anxiety sensitivity, symptoms of depression and anxiety, alcohol and other substance use, have been shown to be related to non-usage attrition in face-to-face smoking interventions (e.g., Belita and Sidani, 2015; Kahler et al., 2009; Langdon et al., 2016; López-Torrecillas et al., 2014). However, these psychological factors have not yet been investigated in web-based smoking cessation interventions. Furthermore, these previous studies used a variable-centered analysis approach such as multiple regression, which aimed at investigating how individual factors were related to intervention non-usage attrition. A caveat of this approach is that it assumes that the data is collected from a homogeneous population (Laursen and Hoff, 2006). As mentioned above, intervention users have been described as rather heterogeneous (e.g., Batra et al., 2008; del Río et al., 2011). Therefore, the determinants of non-usage attrition may differ between subtypes and it is possible that multiple determinants of non-usage attrition interact with each other in a specific subtype of intervention users. Thus, to capture the combination of multiple determinants of non-usage attrition within individuals, a person-centered analysis approach such as clustering-based techniques is more appropriate.

The aim of this study was two-fold: (1) to identify and describe a multi-dimensional typology of smokers participating in a web-based smoking cessation intervention program, and (2) to explore the predictive value of the smoker subtypes on non-usage attrition (i.e., early dropout times). The first aim was addressed with a clustering analysis and the second aim was with a survival analysis to predict time until dropout from intervention. To this end, we conducted secondary analyses of the data collected in a randomized controlled trial (RCT). In this RCT, the individual and combined effects of two varieties of web-based Cognitive Bias Modification (CBM), being Attentional Bias Modification (AtBM) and Approach Bias Modification (ApBM), were examined in adult smokers (Wen et al., 2020). This RCT had a very low usage rate (on

the contrary: a very high non-usage attrition rate): only 10.7% (54/504) of the participants completed the intervention (i.e., 11 CBM training sessions). We have proposed several possibilities to explain the high non-usage attrition rates in this RCT (more detailed and relevant comments can be found in the Discussion section of both this report and Wen et al., 2020), one of which could be the "*one-size-fits-all*" approach we have used to develop the intervention program (i.e., developing and providing an intervention for all participants without taking into account participants' individual differences in their characteristics, treatment needs and preferences, or severity of disorder symptoms). The findings of this study may identify different subtypes of smokers with different characteristics and risks of non-usage attrition, which may increase adherence and engagement in further web-based smoking intervention studies that are tailored to their needs.

2. Methods

2.1. Study overview

This study concerns secondary analyses of data from an RCT investigating the individual and combined effects of two varieties of web-based CBM, AtBM and ApBM, in adult smokers. Details about the study design, procedure, and intervention contents of this RCT can be found elsewhere (Wen et al., 2020). These interventions were designed to specifically change maladaptive smoking-related cognitive biases (i.e., attentional and approach biases toward smoking-related cues), which are thought to play an important role in the maintenance of smoking. In brief, this RCT employed a 2 (AtBM: active vs. sham) $\times$ 2 (ApBM: active vs. sham) factorial design, resulting in four intervention conditions. The active-AtBM was used to train participants to consistently shift their attention away from smoking-related pictures and toward neutral pictures, in order to reduce their smoking-related attentional bias. The active-ApBM was used to train participants to consistently avoid smoking-related pictures and approach neutral pictures, in order to reduce smoking-approach associations and in turn to reduce smoking-related approach biases.

During the first visit, participants registered on the study website, were randomized to one of the four intervention conditions, submitted informed consent, completed a baseline assessment, and received brief tailored feedback to improve their motivation to quit smoking before the intervention. All eligible participants were invited to return to the website to complete 11 CBM training sessions (of the versions of their condition) and to complete five other main assessments throughout the study (i.e., at mid-training after the 5th training session, at post-training after the 10th training session, and follow-ups at 1-, 2-, and 3-months). The study procedure was fully automated with web-based training sessions, and all assessment sessions self-assessed via web-based questionnaires and computerized tasks. Participants were allowed to train daily and could self-arrange their training schedule, but had to complete all trainings and assessments (if they missed one session, they then were removed from this study). During the intervention, participants could contact researchers for questions or technical problems and received multiple reminder emails if they forgot to complete a training or assessment session within 30 days. Participants were not compensated for participating in this study, because they received some free intervention from this study and we aimed to recruit participants with at least some motivation to quit smoking (and not only for financial incentives). The RCT protocol was approved by the Ethics Review Board of the Faculty of Social and Behavioral Science, University of Amsterdam (reference number: 2013-DP-3047) and was registered in the Dutch Trial Register (NTR4678).

2.2. Participants

From 2013 to 2018, participants were recruited across the Netherlands through our lab website (http://www.impliciet.eu/), press

releases (e.g., TV interview, newspaper, popular science book; Wiers, 2013), and word-of-mouth communication. As the RCT concerned a self-help intervention open to all adults, there were no specific inclusion criteria, except for being 18+ years old and able to understand Dutch. In total, 749 eligible participants submitted a consent form and started the baseline assessment, constituting the final analytical sample for this study.

2.3. Measures

2.3.1. Clustering indicators

Baseline measures of the RCT were used to identify subtypes of smokers, which grouped into six domains: demographics, smoking history and smoking-related behaviors, substance use-related personality factors, depression severity, alcohol and other substance use, and cognitive-motivational variables related to smoking cessation. As described in the Introduction, all these variables have differentiated smokers in previous studies and have been used to understand individual differences in non-usage attrition in smoking cessation programs.

2.3.1.1. Demographics. Demographics included *age, gender, the highest completed education level* (low: primary school/basic vocational school, medium: secondary vocational school/high school degree, high: higher vocational school/university degree), *marital status* (married vs. others), and *household income/month* (<€2000, €2000-€3000, vs. >€3000).

2.3.1.2. Smoking history and smoking-related behaviors. Smoking history and smoking-related behaviors included duration of smoking in years, daily cigarette consumption, tobacco dependence, and smoking-related health complaints. *Duration of smoking* was computed by subtracting the age at onset of regular cigarette smoking from the current age. The age at onset of regular cigarette smoking was measured by one item "how old were you when you started smoking daily?". *Daily cigarette consumption* was measured by one item "how many cigarettes do you currently smoke per day?". *Tobacco dependence* was measured with the 6-item Modified Fagerström Tolerance Questionnaire (mFTQ; Prokhorov et al., 2000). The weighted sum score was calculated to indicate the level of tobacco dependence in this study ($\alpha = 0.72$), which ranged from 0 to 6, with a higher score reflecting high levels of tobacco dependence. *Smoking-related health complaints* were measured by one item "have you ever had any of the following smoking-related illnesses?". The answer options included respiratory problems (yes vs. no), and difficulty with circulation (yes vs. no).

2.3.1.3. Substance use-related personality factors. Substance use-related personality factors were measured with the 23-item Substance Use Risk Profile Scale (SURPS; Woicik et al., 2009), which consisted of four subscales: *hopelessness, anxiety sensitivity, impulsivity,* and *sensation seeking.* Four subscale scores were computed, respectively, with a mean item score for each subscale ranging from 1 to 4. Higher scores reflected high levels of the corresponding personality factor. In this study, the Cronbach's alpha (α) for the four subscales were 0.90, 0.67, 0.68, and 0.66, respectively.

2.3.1.4. Depression severity. *Depression severity* was measured using the 7-item Beck Depression Inventory Fast Screen (BDI-FS; Poole et al., 2009). The sum score was calculated to indicate the severity of depression symptoms ($\alpha = 0.82$), which ranged from 0 to 21, with 0–3 reflecting minimal depression, 4–6 mild depression, 7–9 moderated depression, and 10–21 severe depression.

2.3.1.5. Alcohol and other substance use. Alcohol and other substance use was measured with the Core Alcohol and Drug Survey (CADS; Presley et al., 1994). Participants were asked to indicate their frequency of use of alcohol, cannabis, analgesics (i.e., sedatives and opiates), and

stimulants and other drugs (i.e., cocaine or crack, XTC, stimulants or amphetamines, other club or party drugs, hallucinogens, and volatiles) without doctors' prescription in the last month. Additionally, binge drinking behaviors were also measured by one item "how many days in the last month (last 30 days) did you have more than 5 glasses (for a man) or 4 glasses (for a woman) on one occasion?". Frequency of use was coded as follows: *alcohol use* (0, 1–20, 21–40, >40 times), *binge drinking* (0, 1–4, >4 days), and *cannabis, analgesics, stimulants and other drugs use* (0, 1–10, >10 times).

2.3.1.6. Cognitive-motivational variables related to smoking cessation. Cognitive-motivational variables related to smoking cessation included lifetime quit attempts, readiness to change, and confidence to quit smoking. *Lifetime quit attempts* were measured by one item: "how many quit attempts have lasted longer than 24 hours in your lifetime?". *Readiness to change* was measured with the 12-item Readiness to Change Questionnaire (RCQ; Defuentes-Merillas et al., 2002). The sum score was calculated to indicate the level of readiness to change ($\alpha = 0.66$), which ranged from -24 to 24, with a higher score reflecting high levels of readiness to change. *Confidence to quit smoking* was measured with a Visual Analogue Scale (VAS). Participants were required to answer "how confident are you that you can permanently stop smoking?" on the VAS from 1 (not confident at all) to 10 (very confident).

2.3.2. The measure of non-usage attrition

Non-usage attrition was defined as dropping out during the CBM intervention before all training sessions were completed. Participants were classified as a non-user during the intervention if they stopped using it (i.e., once participants did not return to the website within 30 days since their last visit, either to receive a training session or to complete an assessment session, they were excluded from the intervention and could not return to the website any more). The last training or assessment time-point completed by the participant before being classified as a non-user was then considered the moment the participant dropped out of the intervention, and we counted the number of sessions completed up to this moment.

2.4. Data analyses

Not all participants in the final analytical sample ($N = 749$) completed all the measures used to identify subtypes of smokers, resulting in the percentage of missing data ranged from 0.9% to 13.4%. Because Cluster-based analysis cannot handle missing data, missing data were multiply imputed by using *mice* package in R (version 3.8.0; van Buuren and Groothuis-Oudshoorn, 2011) with Predictive Mean Matching (PMM) method, creating 50 imputed data sets. Given that it is possible to obtain multiple different cluster solutions based on the 50 imputed data sets but it is not possible to pool the results of multiple different cluster solutions (Bock, 2021), *sjmisc* package in R (version 2.8.7; Lüdecke, 2018) was used to merge the 50 imputed data sets into a single data set for cluster analysis as follows: each of the missing values in the original data set was filled in with the most frequent imputed value of the 50 imputed data sets. The resulting data set was then used in subsequent steps of the analysis.

To identify the smoker subtypes, we chose a two-step cluster analysis (Norusis, 2008; Walsh et al., 2010) because (a) it is an exploratory procedure for identifying natural groups in a set of data where the number of clusters cannot be determined in advance, and (b) it is the only type of cluster analysis that can handle the combination of continuous and categorical data. Twenty-two variables were entered as clustering indicators. Before the analysis, all continuous measures were standardized. In the first step, the original cases were assigned to "pre-clusters" by constructing a cluster features tree. In the second step, the pre-clusters were clustered with the standard hierarchical clustering algorithm. All the analyses were performed using the log-likelihood

distance measure to reveal natural clusters. Due to the exploratory nature of this study, we allowed the two-step cluster analysis to determine the optimal number of clusters automatically. The auto-clustering procedure produced a range of solutions (15 as default), and we used Bayesian Information Criterion (BIC) fit and Ratio of Distance Measures to determine the number of clusters to retain. Specifically, we first picked a solution based on the lowest BIC values, then adjusted the solution by taking into account solutions with a large Ratio of Distance Measures.

Once the final cluster solution was selected, three required measures were used to validate the results (Norusis, 2008; Walsh et al., 2010). First, the silhouette measure of cohesion and separation was required to be at or above zero (with the highest being 1.0) to ensure that there was some distance between clusters. Second, one-way ANOVAs and Chi-square tests were performed on continuous and categorical clustering indicators, respectively, to identify the importance of individual clustering indicators in the clustering procedure. Post-hoc analyses were performed on the most important clustering indicators (i.e., those being statistically significant in the overall test) to clearly point out between which clusters they differed, with pairwise comparisons and multinomial analyses on continuous and categorical clustering indicators, respectively. Third, split-half cross-validation of the results was conducted to confirm the reliability of the final cluster solution. The full sample was randomly split into two halves by using the *caTools* package in R (version 1.18.0; Tuszynski, 2020), and the same two-step cluster analysis procedures described above were performed in the two sub-samples. If the same number of clusters was found in both the final and split cluster solutions, and the characteristics and significance clustering indicators of the solutions were similar, validation was confirmed. We also calculated Cohen's Kappa (k) index to indicate the level of agreement of assigning participants to the same clusters in the final and split cluster solutions.

To explore the smoker subtypes at a higher risk for non-usage attrition (i.e., earlier dropout time), we conducted a discrete-time survival analysis to predict time until dropout by using Cox proportional hazards regression. The time variable was the total number of training and assessment sessions completed by the participants, and non-usage was considered as a failure. The outcome concerned time-to-event data, where the event was the dropout. Thus, in case that participants did not drop out of the intervention, the outcome was censored. In the survival analysis model, we used the identified smoker clusters (i.e., the final cluster solution) as a predictor, and we included the intervention condition as a covariate. Given that the proportional hazard assumption is made to the Cox proportional hazards regression, before the analysis, we conducted an assumption test by adding interaction terms of final cluster solution × time and of intervention condition × time in the survival analysis model. If significant interaction effects were found, additional time-dependent covariates would be added to the survival analysis model.

All statistical analysis were performed by using SPSS 22.0 (IBM, 2013). An alpha of 0.05 (two-sided) was applied to all tests of statistical significance.

3. Results

3.1. Sample description

Characteristics of the final sample can be found in Table 1. To test for the representativeness of our final sample, we compared our sample to samples who participated in prior published RCTs of web-based smoking interventions (including both motivational and cognitive-behavioral strategies-based and CBM-based interventions) which were conducted in the Netherlands from 2013 to 2016 (see Cheung et al., 2017 for a review). We found that our final sample had similar characteristics in terms of demographics and variables related to smoking as participants in these previous studies, except for education. Our final sample

Table 1

Descriptive statistics of clustering indicators in the full sample and across clusters, and cluster comparison.

Clustering indicators	Full sample ($N = 749$)	Cluster 1 ($n = 189$, 25.2%)	Cluster 2 ($n = 307$, 41.0%)	Cluster 3 ($n = 253$, 33.8%)	$F(df_1, df_2)/$ $\chi^2(df)$	p-Value
Demographics						
Age (years), M (SD)	43.96 (13.84)	30.08 (9.98)$_{ab}$	47.89 (11.28)$_a$	49.55 (12.04)$_b$	194.20 (2, 746)	<0.001
Gender, n (%)					10.67 (2)	0.005
Male	269 (35.9)	72 (38.1)$_1$	126 (41.0)$_1$	71 (28.1)$_1$	–	–
Female	480 (64.1)	117 (61.9)$_a$	181 (59.0)$_b$	182 (71.9)$_{ab}$	–	–
The highest completed education level, n (%)					34.15 (4)	<0.001
Primary school/basic vocational school	67 (8.9)	11 (5.8)$_1$	13 (4.2)$_1$	43 (17.0)$_1$	–	–
Secondary vocational school/high school degree	138 (18.4)	40 (21.2)$_1$	50 (16.3)$_1$	48 (19.0)$_1$	–	–
Higher vocational school/university degree	544 (72.6)	138 (73.0)$_a$	244 (79.5)$_b$	162 (64.0)$_{ab}$	–	–
Marital status, n (%)					128.95 (2)	<0.001
Not married	548 (73.2)	185 (97.9)$_1$	162 (52.8)$_1$	201 (79.4)$_1$	–	–
Married	201 (26.8)	4 (2.1)$_a$	145 (47.2)$_a$	52 (20.6)$_a$	–	–
Household income/month, n (%)					306.79 (4)	<0.001
<€2000	246 (32.8)	125 (66.1)$_1$	3 (1.0)$_1$	118 (46.6)$_1$	–	–
€2000–€3000	187 (25.0)	37 (19.6)$_1$	76 (24.8)$_1$	74 (29.2)$_1$	–	–
>€3000	316 (42.2)	27 (14.3)$_a$	228 (74.3)$_a$	61 (24.1)$_a$	–	–
Smoking history and smoking-related behaviors						
Duration of smoking in years, M (SD)	27.44 (14.04)	14.33 (10.62)$_{ab}$	31.06 (11.89)$_a$	32.85 (12.45)$_b$	158.21 (2, 746)	<0.001
Daily cigarette consumption, M (SD)	16.19 (8.87)	13.20 (7.69)$_a$	15.22 (8.00)$_a$	19.60 (9.61)$_a$	34.00 (2, 746)	<0.001
mFTQ (0–6), M (SD)	3.12 (1.63)	2.67 (1.71)$_a$	2.98 (1.51)$_b$	3.64 (1.60)$_{ab}$	22.22 (2, 746)	<0.001
Smoking-related health complaints, n (%)					21.35 (2)	<0.001
None	572 (76.4)	160 (84.7)$_1$	243 (79.2)$_1$	169 (66.8)$_1$	–	–
Respiratory problems and/or difficulty with circulation	177 (23.6)	29 (15.3)$_a$	64 (20.8)$_b$	84 (33.2)$_{ab}$	–	–
Substance use-related personality factors						
Hopelessness (1–4), M (SD)	2.07 (0.66)	1.98 (0.60)$_a$	1.85 (0.57)$_b$	2.40 (0.67)$_{ab}$	58.34 (2, 746)	<0.001
Anxiety sensitivity (1–4), M (SD)	2.53 (0.59)	2.47 (0.53)$_a$	2.45 (0.61)$_b$	2.68 (0.57)$_{ab}$	12.22 (2, 746)	<0.001
Impulsivity (1–4), M (SD)	1.94 (0.54)	2.03 (0.48)$_a$	1.86 (0.56)$_{ab}$	1.98 (0.54)$_b$	6.55 (2, 746)	0.002
Sensation seeking (1–4), M (SD)	2.22 (0.64)	2.58 (0.62)$_a$	2.17 (0.57)$_a$	2.02 (0.61)$_a$	48.81 (2, 746)	<0.001
Depression severity						
BDI (0–21), M (SD)	3.85 (3.34)	3.80 (3.05)$_a$	2.71 (2.79)$_a$	5.27 (3.63)$_a$	45.63 (2, 746)	<0.001
Alcohol and other substance use						
1-month alcohol use, n (%)					238.07 (6)	<0.001
0 times	90 (12.0)	1 (0.5)$_a$	15 (4.9)$_a$	74 (29.2)$_a$	–	–
1–20 times	391 (52.2)	159 (84.1)$_1$	167 (54.4)$_1$	65 (25.7)$_1$	–	–
21–40 times	141 (18.8)	20 (10.6)$_1$	85 (27.7)$_1$	36 (14.2)$_1$	–	–
>40 times	127 (17.0)	9 (4.8)$_1$	40 (13.0)$_1$	78 (30.8)$_1$	–	–
1-month binge drinking, n (%)					266.04 (4)	<0.001
0 days	250 (33.4)	9 (4.8)$_a$	94 (30.6)$_a$	147 (58.1)$_a$	–	–
1–4 days	292 (39.0)	122 (64.6)$_1$	166 (54.1)$_1$	4 (1.6)$_1$	–	–
>4 days	207 (27.6)	58 (30.7)$_1$	47 (15.3)$_1$	102 (40.3)$_1$	–	–
1-month cannabis use, n (%)					126.67 (4)	<0.001
0 times	569 (76.0)	94 (49.7)$_a$	246 (80.1)$_a$	229 (90.5)$_a$	–	–
1–10 times	122 (16.3)	77 (40.7)$_1$	38 (12.4)$_1$	7 (2.8)$_1$	–	–
>10 times	58 (7.7)	18 (9.5)$_1$	23 (7.5)$_1$	17 (6.7)$_1$	–	–
1-month analgesics use, n (%)					55.60 (4)	<0.001
0 times	671 (89.6)	150 (79.4)$_a$	296 (96.4)$_a$	225 (89.6)$_a$	–	–
1–10 times	58 (7.7)	35 (18.5)$_1$	9 (2.9)$_1$	14 (5.5)$_1$	–	–
>10 times	20 (2.7)	4 (2.1)$_1$	2 (0.7)$_1$	14 (5.5)$_1$	–	–
1-month stimulants and other drugs use, n (%)					168.03 (4)	<0.001
0 times	633 (84.5)	108 (57.1)$_a$	282 (91.9)$_a$	243 (96.0)$_a$	–	–
1–10 times	101 (13.5)	75 (39.7)$_1$	25 (8.1)$_1$	1 (0.4)$_1$	–	–
>10 times	15 (2.0)	6 (3.2)$_1$	0 (0.0)$_1$	9 (3.6)$_1$	–	–
Cognitive-motivational variables related to smoking cessation						
Lifetime quit attempts (times), M (SD)	4.12 (3.68)	3.24 (2.48)$_{ab}$	4.53 (3.83)$_a$	4.28 (4.12)$_b$	7.72 (2, 746)	<0.001
RCQ (−24–24), M (SD)	11.71 (5.71)	11.66 (5.13)	11.39 (6.14)	12.13 (5.59)	1.18 (2, 746)	0.307
Confidence to quit (0–10), M (SD)	5.81 (2.02)	5.90 (1.80)	5.95 (2.05)	5.59 (2.11)	2.49 (2, 746)	0.084

Notes: mFTQ = Modified Fagerström Tolerance Questionnaire. BDI = Beck Depression Inventory Fast Screen. RCQ = Readiness to Change Questionnaire. Letter subscripts a and b: M (SD) or n (%) sharing a letter subscript are significantly different from each other based on post-hoc analyses ($p < 0.05$). Number subscript 1: M (SD) or n (%) with the number subscript 1 indicates the reference categories of the categorical variables used in the multinomial analyses; the multinomial analyses were used in the post-hoc analyses to test the cluster differences as a function of the categorical variables.

included a larger proportion of highly educated smokers (i.e., at least higher vocational school/university degree) than these previous studies (72.6% vs. 20.2%–38.7%). Overall, our final sample's average age was 43.96 ($SD = 13.84$); females were over-represented (64.1%); most participants were highly educated (72.6%); they had smoked on average for 27.44 years ($SD = 14.04$), used to smoke 16.19 cigarettes/day ($SD = 8.87$), reported medium levels of tobacco dependence (M (SD) = 3.12

(1.63); range from 0 to 6), and showed high levels of readiness to change (M (SD) = 11.71 (5.71); range from −24 to 24). Additionally, about a quarter of the participants (23.6%) reported smoking-related health complaints.

3.2. Selection and validation of the final cluster solution

The cluster analysis revealed three clusters (see Table S1 in the Supplementary Results for auto-clustering statistics). First, the analysis produced a silhouette measure of cohesion and separation of 0.1, suggesting that there was some distance between clusters. Next, one-way ANOVAs and Chi-square tests confirmed that most of the clustering indicators varied between clusters (see Table 1), suggesting that the clusters were relatively clearly characterized. Finally, the split sub-samples represented the final cluster solution, with some small changes (see Tables S2 and S3 in the Supplementary Results for descriptive statistics of clustering indicators in the two sub-samples and across clusters). Additionally, reliability analyses indicated a substantial level of agreement ($k = 0.71$ and 0.65; Alman, 1991) regarding the assignment of participants to the same clusters in the final and split cluster solutions. Specifically, 80.7% and 70.1% of the sample were reclassified correctly when conducted in each half of the sample separately, suggesting adequate robustness of the final cluster solution (see Table S4 in the Supplementary Results for split-half cross-validation of the final cluster solution). Based on these results, thus, we accepted the three-cluster solution.

3.3. Description of the smoker typology

Table 1 depicts the pattern of raw mean and modal responses on the clustering indicators in the final analytic sample and across clusters. Fig. 1 shows the pattern of standardized mean and modal responses on the clustering indicators across clusters. The latter helps visualizing the comparison of the clustering indicators on the same scale and the differences on the clustering indicators across clusters. Overall, the clusters differed on all the clustering indicators, except for readiness to change and confidence to quit smoking.

Cluster 1 was the smallest in this study, which included 25.2% (189/ 749) of the participants in the final sample. It mainly consisted of young adult smokers in their early 30s. Most participants were female and were highly educated. They were most likely to be unmarried (although not necessarily single) in the final sample. Participants in this cluster smoked for significantly fewer years than those in the other two clusters and could be characterized as light-to-moderate smokers. Specifically, on average, they smoked around half a pack of cigarettes per day and reported low-to-moderate levels of tobacco dependence. Additionally, participants in this cluster showed moderate-to-high levels of sensation seeking (significantly higher than those in Clusters 2 and 3); showed moderate levels of impulsivity (significantly higher than those in Cluster 2); and were significantly more likely than Clusters 2 and 3 to use multiple substances in the past month, including use of alcohol (99.5% drank and 95.2% reported binge-drinking), cannabis (50.3%), analgesics (20.6%), and stimulants and other drugs (42.9%).

Cluster 2 was the largest in this study, which included 41.0% (307/ 749) of the participants in the final sample. It was primarily middle-aged smokers in their late 40s, and contained a slightly greater proportion of females than males. Compared with the other two clusters, Cluster 2 included a significantly greater proportion of married participants (47.2%) and participants with a monthly household income above the
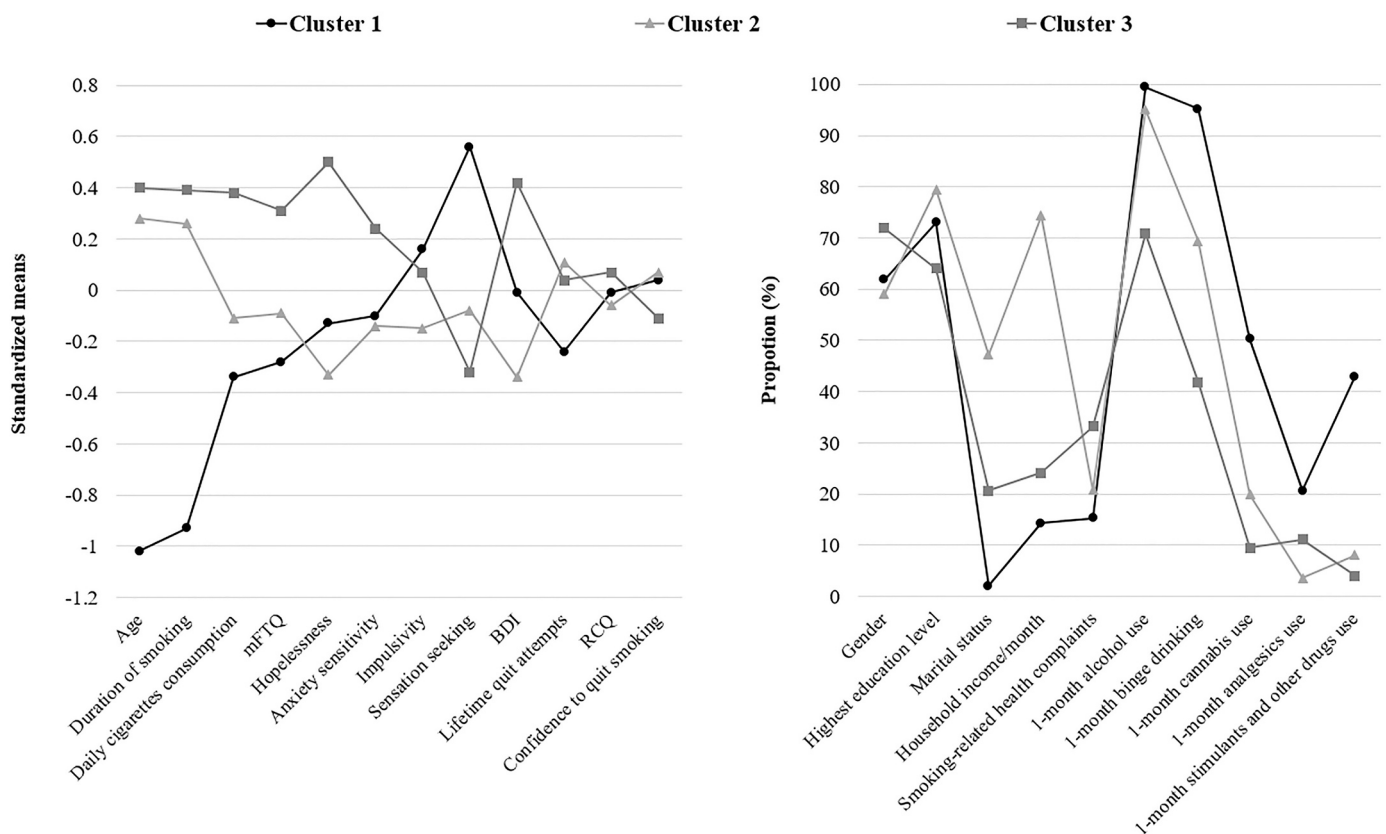

Fig. 1. Standardized mean and modal responses on the clustering indicators across clusters.
Notes: mFTQ = Modified Fagerström Tolerance Questionnaire. BDI = Beck Depression Inventory Fast Screen. RCQ = Readiness to Change Questionnaire. "Female" category was shown for gender. "Higher education" category was shown for the highest educational level. "Married" category was showed for marital status. ">€3000" category was shown for household income/month. "Having respiratory problems and/or difficulty with circulation" category was shown for smoking-related health complaints. "Use" category was shown for 1-month alcohol, cannabis, analgesic, and stimulant and other drugs use and 1-month binge drinking. Clustering indicators of highest education level, household income/month, alcohol and other substance use were modelled as ordinal variables in the cluster analysis but coded as binary in this figure for ease of presentation.

national modal income of about €3000 (74.3%), indicating a relatively high socio-economic status (SES). Although participants in this cluster had smoked for 2/3 of their life-time (M (SD) = 31.06 (11.89) years), they were moderate smokers. Specifically, on average, they smoked 15.22 cigarettes per day and reported medium levels of tobacco dependence. Regarding other substance use in the past month, participants in this cluster mainly used alcohol (95.1%) and hardly use other drugs.

Cluster 3 included 33.8% (253/749) of the participants in the final sample. Similar to participants in Cluster 2, they were middle-aged smokers in their late 40s. This cluster contained a significantly greater proportion of females (71.9%) and a significantly smaller proportion of highly educated participants (64%) than the other two clusters. Although participants in this cluster were similar in age to those in Cluster 2, they were significantly less likely to be married than Cluster 2 and they had a significantly lower household income than Cluster 2 (only 24.1% reported household income/month above the national modal income of about €3000), indicating that this cluster was characterized by a relatively low SES. Participants in this cluster were long-term heavy smokers: on average, they smoked about one pack of cigarettes per day and reported medium-to-high levels of tobacco dependence. Additionally, they were significantly more likely than Clusters 1 and 2 to report smoking-related health complaints (including respiratory problems and difficulty with circulation: 33.2%). Notably, participants in this cluster showed moderate-to-high levels of hopelessness and anxiety sensitivity (significantly higher than those in Clusters 1 and 2); showed moderate levels of impulsivity (significantly higher than those in Cluster 2); and showed mild levels of depression symptomatology on average (significantly higher than those in Clusters 1 and 2). Regarding other substance use in the past month, similar to those in Cluster 2, participants in this cluster mainly used alcohol (70.8%). But notably, they were significantly more likely to show heavy drinking patterns than those in Clusters 1 and 2: 45% used alcohol more than 20 times and 40.3% showed binge drinking behaviors more than 4 days in the past month.

3.4. Smoker subtypes related to non-usage attrition

The results of the assumption test showed that both the predictor of final cluster solution and the covariate of intervention condition meet the proportional hazard assumption (final cluster solution × time: $\chi^2(1)$ = 2.83, p = 0.093; intervention condition × time: $\chi^2(1)$ = 0.10, p = 0.748). Thus, no additional time-dependent covariates were added to the survival analysis model. Discrete-time survival analysis showed that smoker cluster membership was a significant predictor of time until dropout (omnibus test: $\chi^2(2)$ = 20.90, p < 0.001, R^2 = 0.26), after controlling for intervention condition (omnibus test: $\chi^2(3)$ = 1.53, p = 0.677, R^2 = 0.02), suggesting differences in time until dropout across the clusters. Given that the clusters of smokers were not evenly distributed across intervention conditions ($\chi^2(6)$ = 14.23, p = 0.027) with Cluster 1 were more likely to be assigned to the sham CBM training condition, we further conducted an exploratory analysis by adding the interaction terms of final cluster solution by intervention condition in the survival analysis model to investigate the impact of the intervention condition. This exploratory analysis resulted in a non-significant interaction effect of final cluster solution and intervention condition on time until dropout (omnibus test: $\chi^2(6)$ = 4.46, p = 0.615, R^2 = 0.06). Thus, the effects of smoker cluster membership on time until dropout was not influenced by the intervention condition assignment.

Post-hoc analyses indicated that regardless of which intervention condition participants were in, participants in Cluster 1 showed a 51% higher risk for earlier dropout time than Cluster 2 (Wald test: $\chi^2(1)$ = 18.29, p < 0.001; adjusted Hazard Ratio ($HR_{adjusted}$) = 1.51, *95% CI* = [1.25, 1.83]) and showed a 52% higher risk for earlier dropout time than Cluster 3 (Wald test: $\chi^2(1)$ = 17.33, p < 0.001; $HR_{adjusted}$ = 1.52, *95% CI* = [1.25, 1.86]). Clusters 2 and 3 did not differ in time until dropout

(Wald test: $\chi^2(1)$ = 0.01, p = 0.934; $HR_{adjusted}$ = 0.99, *95% CI* = [0.83, 1.18]).

The actually observed non-usage attrition curve across clusters can be found in Fig. 2. Although in all three clusters the highest proportion of participants stopped using the intervention during the first three training sessions, Cluster 1 showed a quicker dropout pattern than Clusters 2 and 3. Specifically, 69.8%, 40.7% and 40.3% of participants dropped out in the first training session for Clusters 1, 2, and 3, respectively; and 88.9%, 69.7%, and 69.6% of participants dropped out between the first and the third training session for Clusters 1, 2, and 3, respectively (see Fig. 2). In all three clusters, the proportion of participants who stopped using the intervention decreased gradually from the fourth training session to the eighth training session and remained steady until the end of the intervention (the retention rates at 3-month follow-up were 3.2%, 7.2%, and 7.1% for Cluster 1, 2, and 3, respectively; see Fig. 2).

4. Discussion

In this study, we first identified multi-dimensional typologies of smokers participating in an RCT of a web-based smoking cessation intervention (i.e., web-based CBM), which we then related to non-usage attrition. The ultimate objective of this study was to stimulate future tailored web-based smoking cessation interventions to better fit different user profiles.

4.1. Main findings

The results of the cluster analysis indicated three clusters of smokers, which differed on a broad range of characteristics. Participants in Cluster 1 were young light-to-moderate smokers who were likely at the early stage of their smoking career and were likely poly-substance users. Cluster 1 showed relatively high levels of sensation seeking, a personality trait characterized by the desire for intense and new experiences, which has been related to elevated (poly) substance use and self-reported motives for drug use that involve enhancement of positive affect (Schlauch et al., 2015; Woicik et al., 2009). Cluster 1 also showed moderate levels of impulsivity. Although the SURPS questionnaire used in this study cannot distinguish between multiple facets of impulsivity, based on their sensation-seeking characteristics, Cluster 1 might be characterized by a positive urgency trait: a tendency to act rashly in response to rewards/positive moods (Spillane et al., 2010). Thus, taken together, it seems reasonable to infer that Cluster 1 smoked and used multiple other drugs mainly for a euphoric effect. The overall characteristics of Cluster 1 may suggest that this is a group of young adult smokers who are vulnerable to engage in health-risk behaviors, or where smoking and drug use is part of their risk-taking and hedonistic lifestyle (c.f., Rose et al., 2007).

Participants in Cluster 2 comprised middle-aged moderate-to-heavy smokers with a relatively high SES. In addition to cigarette smoking, they consumed alcohol often, but did not often use other drugs. Since Cluster 2 had smoked for 2/3 of their life-time (around 31 years), their smoking behaviors might have become habitual over time, likely (partly) intertwined with their alcohol use. Additionally, although Cluster 2 were long-term smokers, they only showed moderate levels of tobacco dependence. This may further suggest that their smoking behaviors are likely behavioral habits, such as hand-to-month movements and smoking during a work break or after a meal, in addition to smoking to obtain pharmacological effects (Elfeddali et al., 2013).

Participants in Cluster 3 showed relatively high levels of hopelessness, anxiety sensitivity, and depression, and were more likely than the other two clusters to binge drink, in addition to cigarette use. Since hopelessness and anxiety sensitivity represent personality dimensions consonant with individual susceptibility to the negative reinforcement properties of various substances as a means of coping with negative affect (Schlauch et al., 2015; Woicik et al., 2009), Cluster 3 seems to
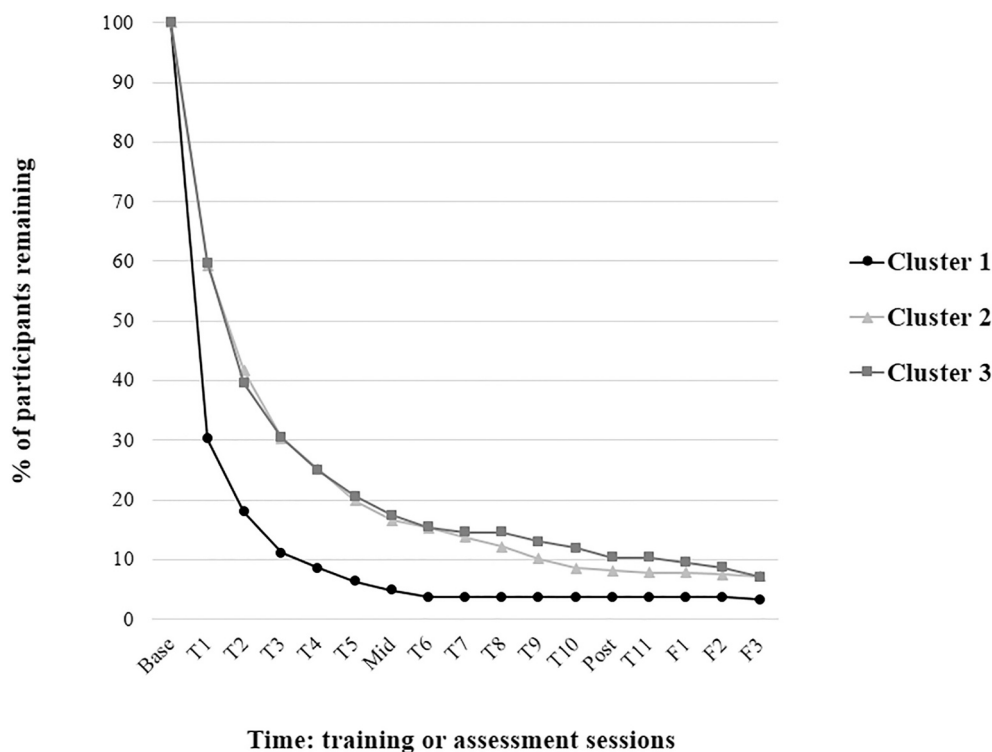
Fig. 2. Non-usage attrition curve across clusters.

Notes: Base = Baseline assessment. Mid = Mid-training assessment. Post = Post-training assessment. F1, F2, F3 = Follow-up assessments at 1-, 2-, and 3-months. T1-T11 = Training session 1 to 11.

primarily include negative-affect smokers who smoke (and drink) for self-medication, in order to reduce their depressive symptoms and other negative affect. Additionally, Cluster 3 contained mostly female middle-aged smokers with relatively low SES. These results are in line with previous studies showing that being female and having a low SES are risk factors for depression (Back and Lee, 2011; Koster et al., 2006). Furthermore, Cluster 3 comprised of heavy smokers, who were more likely to report smoking-related health complaints. This result is in line with previous findings that depressed smokers may continue smoking and are less likely to quit (Murphy et al., 2003), so they tend to report higher rates of smoking behavior and tobacco dependence (John et al., 2004). But, it should be noted that although Cluster 3 showed the highest levels of depression severity in the whole sample, they only showed mild levels of depression symptomatology on average.

Primarily based on the SURPS questionnaire, we inferred the motives for smoking of the three clusters of smokers. It seems that our results resembled three out of four theory-derived categories of smokers proposed by Tomkins (1966): positive affect smokers (our Cluster 1), habitual smokers (our Cluster 2), and negative affect/depressed smokers (our Cluster 3); the fourth category, which was individuals who smoke for both positive and negative reinforcement was not found here. However, it should be noted that explicit measures of expectancies and motives for smoking were not included in the present study. Although the substance use-related personality factors showed their relevance in the clustering procedure, they were less often to be assessed in many (web-based) studies than the explicit expectancies and motives for smoking. Thus, we recommend that further studies include explicit expectancies and motives for smoking to refine the identified multi-dimensional profiles.

Additionally, compared with previous studies on smoker typologies in general smokers who did not seek help to quit smoking (Cohn et al., 2017; Furberg et al., 2005; Manley et al., 2009; Timberlake, 2008) or in smokers participated in studies on face-to-face smoking cessation interventions (Batra et al., 2008; Del Río et al., 2011), we used a different

sample and included a broader range of participant characteristics to identify subtypes of smokers, which limited the comparability. However, when comparing some individual features between our smoker typology and other multi-dimensional smoker typologies identified in these previous studies, we still found some similarities. For example, Batra et al. (2008) found a typology characterized by low levels of tobacco dependence and craving, and high levels of sensation seeking; Cohn et al. (2017) found a "poly-substance users" typology characterized by young, higly educated, and light-to-moderate smokers; and Furberg et al. (2005) found a typology of extrovert personality traits and light smoking. Our Cluster 1 seems to be consistent with these subtypes of smokers. Additionally, Furberg et al. (2005) also identified a typology comparable to our Cluster 2 smokers, who are long-term smokers with the majority being married (with children), moderate tobacco dependence, and having little depression or anxiety symptoms. Furthermore, almost all these prevous studies on smoker typologies have found a type of "depressive smoker" or "smoker with mood disorders" (Batra et al., 2008; Del Río et al., 2011; Furberg et al., 2005; Manley et al., 2009; Timberlake, 2008), similar to our Cluster 3. Thus, these similarities may still imply a certain degree of consistency in the identified smoker typologies across different studies, contexts, and population of smokers.

Lastly, although the three clusters of smokers identified in this study differed on a broad range of characteristics, highlighting the heterogeneity of smokers participating in web-based smoking cessation programs, they did not really differ on cognitive-motivational variables related to smoking cessation. Although Cluster 1 reported fewer lifetime quit attempts than the other two clusters, this may be the result of their not having smoked for as many years as the other two clusters. Their similar high levels of readiness to change and moderate levels of confidence to quit smoking may reflect that the participants indeed had some motivation to do something about their smoking behavior and therefore enrolled in this web-based study on smoking cessation, especially considering that the participants knew at the beginning that this study did not include any financial incentives for their participation.

Therefore, the sample of this study is likely to be part of the smokers who actively seek help to quit smoking, and thus the null findings on the motivational-cognitive variables related to smoking cessation are not surprising.

The survival analysis results indicated that, compared with Clusters 2 and 3, Cluster 1 showed a 50% higher risk of early dropout of the intervention. The actually observed non-usage attrition curve further revealed that, compared with Clusters 2 and 3, Cluster 1 showed a quicker dropout pattern especially at the early stage of the intervention (i.e., during the first three training sessions). Up to 69.8% of Cluster 1 only made one visit and never returned to the website, even after providing detailed personal information in the registration process and completing an extensive battery of survey instruments. These intervention users have previously been referred to as "one-hit-wonders" (e.g., Saul et al., 2016). Further, up to 88.9% of Cluster 1 left the intervention very early (i.e., at the third intervention session), therefore, they were also part of "early dropouts" (e.g., Batterham et al., 2008). Both "one-hit-wonders" and "early-dropouts" have been identified as users that are more difficult to engage for a longer time in web-based interventions. The result that Cluster 1 was at a higher risk for early dropout may be intervention specific. That said, the web-based CBM program may not meet participants' treatment needs and therefore they might not be satisfied with this intervention. But, given that previous studies have found that smokers who are younger or less addicted to tobacco are more likely to stop using web-based smoking cessation interventions (Cantrell et al., 2016; Graham et al., 2006; Wangberg et al., 2008), Cluster 1 might be a group of smokers that have a "propensity to not comply"; thus, they are not very adherent to web-based smoking cessation interventions in general.

Instead of investigating how individual factors were related to non-usage attrition, this study related multi-dimensional smoker typologies to non-usage attrition. Thus, this study further extended previous findings by showing that younger, highly educated, unmarried, light-to-moderate smokers with hedonistic and risk-taking characteristics might be at a higher risk for non-usage attrition in web-based smoking cessation interventions. To pinpoint the specific reasons why this subtype of smokers is less likely to use web-based smoking cessation interventions, further research is needed.

4.2. Implications for further research

According to user-centered intervention design approaches, understanding the characteristics and needs of the target users is a necessary first step in the design of (digital) intervention or eHealth technology. Some specific design methods have been proposed, such as persona-based design and participatory design (van Gemert-Pijnen et al., 2018). In the intervention development field, the persona can be described as some intervention user groups with typical characteristics, therefore, it can provide useful information for intervention designers to understand their treatment needs therefore further develop tailored interventions to meet their needs. While participatory design focuses on incorporating targeted intervention users' feedback into the intervention design stage in order to develop tailored interventions to meet their needs. Although these ideas and methods are not new, the results of a recent review indicate that they have not yet been used routinely in the intervention design in the addiction field (Zhang and Ying, 2019).

In the large RCT of the web-based CBM, we observed that all three clusters of smokers showed very high non-usage attrition rates over the whole course of the intervention, suggesting that the intervention program was not well accepted in general. As mentioned in the Introduction, one of the reasons for this could be related to the fact that the RCT of the web-based CBM, although based on theory and evidence, was developed with a "*one-size-fits-all*" approach rather than a "*user-centered*" approach. But, it should be noted that the high attrition rates observed in the RCT may be also related to several other factors (detailed discussion can be found in Wen et al., 2020). In summary, these factors included (a)

the CBM tasks had an intrinsic repetitive nature; thus, participants reported that it was boring; (b) to train participants in a more implicit manner, the CBM tasks used indirect instructions to guide participants to respond to an irrelevant feature of the stimuli in the training; thus, participants reported low levels of credibility of the training, (c) the lack of credibility of the CBM training may have led participant to perceive that they were in the control conditions and to feel disappointed and therefore to discontinue with the intervention; (d) the intervention program included repeated measures to monitor relevant cognitive and behavioral changes, which may have taxed participants' motivation to train; and (e) the intervention did not include some basic principles of "treatment", such as therapists' (face-to-face or remote) supports, and feedback or reinforcement for participants' performance. Although many general recommended strategies may counter these problems to increase the adherence and engagement levels in the RCT, such as providing gamifying intervention, clear intervention instruction, contingency management, therapists' supports and feedback, and concision assessments (Boendermaker et al., 2015; Brouwer et al., 2011; Holter et al., 2016; Saul et al., 2016), the results of this smoker profiling study suggests that tailoring the intervention to different intervention users may lead to better results.

The three clusters of smokers found in this study differed on a broad range of characteristics, which reflected different treatment needs. Although all three clusters of smokers showed high non-usage attrition rates, the results of the survival analysis showed that the smoker cluster membership explained 26% of the variance of the outcome of non-usage attrition and revealed that one of the three clusters had a tendency to quit early from the intervention. Taken together, these results support the idea that web-based smoking interventions could be tailored to different smoker subtypes to increase adherence and engagement levels and that certain smoker subtypes may indeed need extra attention from intervention designers to increase overall adherence and engagement levels in web-based smoking interventions.

The three clusters of smokers found in this study could be used for more persona-based intervention design (van Gemert-Pijnen et al., 2018). Based on their characteristics, we could propose some user-intervention matching ideas. Intervention for Cluster 1 (younger, highly educated, unmarried, light-to-moderate smokers with hedonistic and risk-taking characteristics) may need to capitalize on their tendency to "chase the fun and reward" in their life in order to motivate continued participation. Thus, it might be particularly important to provide other sources of fun (e.g., gamifying intervention; Boendermaker et al., 2015) and reward (e.g., contingency management; Saul et al., 2016) in their intervention. Additionally, young adult smokers are less likely to adopt formal smoking cessation interventions (e.g., CBT) than older smokers (Solberg et al., 2007). In this case, brief sessions of web-based psycho-educational coaching on poly substance use might be enough for them, especially considering their low levels of smoking severity and high prevalence of multiple drugs usage. Furthermore, intervention contents for Cluster 1 also could focus on targeting their current hedonistic and risk-taking behaviors or lifestyle by exploring how cessation can broaden their life experiences and achieve self-worth versus focusing solely on the idea of quitting smoking (e.g., Motivational Interviewing; Miller and Rollnick, 2012). Intervention for Cluster 2 (middle-aged, light-to-moderate, habitual smokers with high SES and involved in alcohol use) may mostly need to help them break their smoking habits and simultaneously help them build new adaptive alternative behaviors (e.g., behaviors activation, formation of intention implementation; Armitage, 2008; Kopetz et al., 2017; Wen et al., 2021). Additionally, intervention for Cluster 2 may also need to address their alcohol use, which may impede efforts toward positive smoking behaviors change. Moreover, considering Cluster 2 were more likely to be married, their partner could be involved in their intervention as a form of social and emotional support. Intervention for Cluster 3 (middle aged, heavy smokers with low SES and mild depression) might benefit from stronger focus on emotion regulation and coping. For this purpose, several

evidence-based digitalized interventions could be used such as mindfulness and mood management-based CBT (Gierisch et al., 2012; Hofmann et al., 2010). Besides, given that smoker who are vulnerable to emotional disorders (e.g., depression and anxiety) are less likely to tolerate the distress during the quitting processes, increasing the likelihood of abandoning an intervention program (Baines et al., 2016; Langdon et al., 2016), a more gradual and highly rewarding approach may help Cluster 3 by paying attention to small achievements (e.g., smoking 1 cigarette less) and providing positive feedback promptly (Secades-Villa et al., 2019).

Also, the three clusters of smokers found in this study may be used to guide the formation of focus groups in the participatory intervention design (van Gemert-Pijnen et al., 2018). For example, a brief screening form based on the clusters identified in this study was used to stratify smokers into focus groups that were homogeneous by typology, wherein discussions to identify salient intervention contents and formats were conducted in order to develop more attractive and effective smoking interventions in the web-based context. Additionally, through the focus groups, the intervention designers may obtain more specific treatment needs from the participants, which are not often assessed during a baseline of a web-based smoking intervention, such as digital literacy (c. f., Atkinson et al., 2009). Furthermore, these user-intervention matching ideas we proposed above may form the basic treatment menu, which can help intervention designers initiate and frame the discussion with these focus groups on smoking cessation interventions based on their characteristics. Through the focus groups, this basic treatment menu can be further improved by incorporating their feedback to meet different users' needs.

4.3. Limitations

When interpreting the results of this study, some limitations need to be taken into account. First, this study adopted a clustering-based method to identify smoker subtypes. Clustering is a classification algorithm that ignores the uncertainty in the classification of users into clusters. To counter this issue, more sophisticated methods, such as Latent Class Analysis (LCA) are recommended in the literature. LCA is based on a theoretical model in which there exist real taxa at a level beyond the observed variables (Stanley et al., 2017). However, the data in this study were not collected specifically to identify smokers' typology and we did not have any theory-supported structures of the data set. Therefore, we chose an empirical method of classification (i.e., clustering-based analysis) which is not based on any kind of theory like LCA. Clustering only seeks to group individuals on the basis of the observed variables.

Second, the generalization of the smokers' typology identified in this study may have been limited. In this study, internal cross-validation procedures in the same sample ensured the reliability of the clustering results, yet without guaranteeing external validity. A related limitation involved the self-selected nature of the sample, which may also cause the difficulty of generalizing the identified smokers' typology. Specifically, although this study mirrored previous RCTs of web-based smoking interventions in their over-representation of females and individuals with a strong motivation to quit smoking (see Cheung et al., 2017 for a review), our sample was biased by having more highly educated participants than previous studies. More importantly, the sample in this study consisted of smokers who were interested in and volunteered to participate in an experimental intervention study on smoking cessation, who may differ from those who search for web-based smoking cessation programs "in the real world", such as QuitCoach and Smokefree (i.e., evidence-based (self-help) intervention programs that delivered as public smoking cessation services Bricker et al., 2018b, 2018a). Therefore, the subtype of smokers found in this study cannot be generalized to the field of e-health outside the context of voluntary participation in an RCT. Although there is a need to replicate the results of this study in the field of e-health outside the context of RCTs, our basic ideas of

identifying typologies of intervention users to tailor intervention according to their characteristics may be also applicable to the field of e-health outside the context of RCTs to counter the general issue of intervention non-usage attrition. Given that the web-based smoking cessation programs "in the real world" have the ability and opportunity to collect big data, intervention designers could employ their users' pretreatment characteristics into a clustering algorithm to identify user subtypes, and through which to create a robust menu of tailored interventions.

Third, although addressing the characteristics of intervention users in a web-based smoking intervention (including web-based CBM) may decrease intervention non-usage attrition and thus further increase the effectiveness, it, however, remains a challenge to find a way to assess and include measures of multiple domains related to the multidimensional smoker profiles in a manner that does not burden the participants. For example, to develop a tailored intervention for Cluster 1 smokers to increase overall adherence and engagement levels in web-based smoking interventions, at least six-domain measures (i.e. age, education, marital status, smoking heaviness, hedonism, risk taking) need to be assessed. A general suggestion would be to adopt reliable and valid measures that are as short as possible.

Fourth, in this study, the treatment structure was sequential, that is, participants could not receive the next training/assessment session before completing the previous session; and participants were excluded from the study if they did not finish one training or assessment session, which was different from the interventions where there is no order in the treatment modules and participants can use the intervention whenever they want. Thus, the non-usage attrition patterns observed in this study cannot be generalized to interventions with different structures and use requirements. This also points to the need to replicate the identified cluster of smokers with a high risk of early dropout in other kinds of web-based smoking intervention programs. Additionally, we interpreted the non-usage attrition as an intervention failure. However, there is evidence that a proportion (sometimes as high as a third) of smokers disengaged from a web-based intervention because they succeed in quitting smoking and do not need the intervention anymore (e.g., Saul et al., 2016), suggesting that high levels of attrition are not synonymous with treatment failure in all cases. Exit interviews or brief surveys about reasons or motives to leave the web-based program, should become a routine procedure to better grasp the nuances of non-usage attrition.

4.4. Conclusions

To the best of our knowledge, this study was the first to explore multi-dimensional smoker typologies based on participants' pretreatment characteristics in an RCT of a web-based smoking cessation program and use a person-centered approach to understand the high non-usage attrition issue of such type of interventions. The results indicated the existence of three clusters of smokers, and one cluster was more likely to drop out early than the other two clusters. The three clusters of smokers identified in this study differed on a broad range of characteristics and on intervention non-usage attrition patterns. These results highlight the heterogeneity of smokers participating web-based smoking cessation programs as well as support the idea that web-based smoking interventions need to be tailored to meet the characteristics and needs of each smoker subtype in order to improve adherence levels and ultimately effectiveness. The three clusters of smokers identified in this study could be a useful intervention user segmentation for further tailoring of web-based smoking cessation interventions.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Appendix A. Supplementary results

Supplementary results to this article can be found online at https ://doi.org/10.1016/j.invent.2021.100473.

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