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Detecting Longitudinal Patterns of Daily Smoking Following Drastic Cigarette Reduction

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Abstract

To enhance prolonged smoking cessation or reduction, a better understanding of the process of change is needed. This study examines daily smoking rates following the end of an intensive smoking reduction program originally designed to evaluate the relationship of tobacco biomarkers with reduced levels of smoking. A novel pattern-oriented approach called time-series-based typology is used to detect homogeneous smoking patterns in time-intensively (i.e., 40 occasions) observed smokers (n=57), who were predominantly Caucasian (94.7%), male (52.6%), and on average 47.9 years old (SD=11.3). The majority of the smokers exhibited a change in their daily smoking behavior over the course of 40 days with 47.4% increasing and 40.4% decreasing the number of cigarettes smoked per day, which is contrary to the results a group level approach would have found. Very few smokers (12.3%) maintained their average smoking rate, and exhibited an externally controlled smoking pattern. Trajectory type could be predicted by temporally proximal motivation and self-efficacy variables (($F(4, 106)=3.46$, $p=.011$, $\eta^2=.115$), underscoring their importance in maintaining reduced smoking rates. Time series-based typology demonstrated good sensitivity to the identification of meaningfully different trajectories.

Keywords

time series-based typology; time series analysis; harm reduction; longitudinal smoking patterns; idiographic research

A new wave of behavior change intervention research is beginning that seeks to usher a new generation of more effective, far-reaching, and sustainable interventions into existence (Orleans, 2005; S. D. Solomon, 2005). The creation and dissemination of innovative methodological tools that allow for the analysis of complex longitudinal data is an important part of this new initiative. In this paper, we present an innovative approach to longitudinal data that is based on traditionally used analyses and is thus very accessible to applied researchers. In particular, our paper focuses on detecting longitudinal patterns of daily smoking following drastic cigarette reduction. With most cigarette smokers relapsing within three months of a cessation attempt (Fiore, Smith, Jorenby, & Baker, 1994; Shiffman, 1993), there is a need to improve our understanding of the process of behavior change following smoking reduction and cessation and underlying relapse. To this end, our paper presents the largest time series study of smoking behaviors to date. It is also our starting point for showcasing an innovative and easy to use analytical tool for grouping longitudinal patterns, which we validate in our sample using psychosocial, demographic and physiological variables.

Psychological researchers interested in modeling processes of change over time typically employ either nomothetic (population-level) or idiographic (individual-level) designs. Population-level designs use panel data, collected from a large number of participants typically at a few (i.e., 2 to 5) time points to estimate the adequacy of a growth function for the sample under study. The resulting estimated growth functions are thought to describe all individuals within the sample more or less equally well.

Idiographic designs, on the other hand, focus on individuals rather than populations. Instead of collecting data from a large number of individuals, idiographic studies collect data from a single individual on a large number of occasions. As time is sampled more intensively, change over time can be conceptualized and studied in a variety of innovative ways, including detecting underlying naturalistic processes, characterizing patterns of change over time, and assessing the effects of either a planned or unplanned intervention.

Population-level designs are most often used in the field of substance abuse prevention and intervention and other applied areas of behavioral research because they are believed to maximize the generalizability of the intervention. Idiographic studies, which have limited inter-individual generalizability, have largely been ignored (Molenaar, 2004). Ironically, population-level designs suffer their own lack of generalizability. Specifically, the degree to which individual growth patterns are accurately or adequately represented by population-level functions is limited. For instance, population-level growth functions might fit the overall observed sample of individual growth patterns but fail to describe even a single individual's trajectory. This limitation of population-level estimates is widely recognized, as evidenced by the current popularity of multilevel modeling techniques (McArdle & Epstein, 1987; Meredith & Tisak, 1990). Multilevel models conceptualize inter-individual heterogeneity in intra-individual change as variability around a common trajectory, and thereby simultaneously fit individual and population-level growth functions.

Idiographic designs, for the most part, do not address inter-individual heterogeneity in longitudinal trajectories but rather focus intensively on a single individual (or other 'unit' of interest) over time. One of the most commonly used statistical methods for idiographic studies is time series analysis (e.g., Glass, Willson, & Gottman, 1975; Velicer & Fava, 2003). Time series analysis is similar to a simple regression, except that multiple observations per person are used instead of single observations from multiple persons. Interrupted time series analyses that partition and compare pre- and post-interruption observations are similar to an analysis of variance (ANOVA).

Multiple strategies exist to draw inferences from individual time series to populations of interest. Meta-analysis and pooled time series analysis (Dielman, 1989; Hoeppner, Goodwin, & Velicer, 2003; Hsiao, 1986) provide statistical inference whereas systematic replication (Barlow & Hersen, 1984) provides only logical inference.

A third alternative exists for longitudinal study that focuses neither on the individual nor on a whole population, but instead focuses on the identification of sub-populations of growth patterns. This pattern-oriented approach conceptualizes inter-individual heterogeneity in intra-individual change as being indicative of a limited number of sub-populations characterized by informatively different trajectories (Dumenci & Windle, 2001). The goal of this approach is to identify patterns of change when the existence of subgroups is hypothesized and group membership in these subgroups is *not* known *a priori*. The identification of subpopulation patterns of change are useful to (1) parsimoniously represent individual differences in intra-individual stability and change, (2) evaluate taxonomic developmental theories of change, and (3) facilitate the development of models for early intervention and prevention programs by determining predictors and outcomes specific to a certain growth pattern. In this paper, we showcase a method that can be used to identify subpopulation patterns of change.

Our methodology is based on the widely used cluster analysis. Cluster analysis is an exploratory data-analytic technique ideally suited for the identification of unknown subpopulations. Typically, cluster analysis is based on a set of variables all measured at the same point in time. Dynamic cluster analysis is based on a single variable measured on multiple occasions over time (Huizinga, 1979; Norman, Velicer, Fava, & Prochaska, 1998; Velicer & Rossi, 1986). The resulting clusters are sometimes called *dynatypes*. Longitudinal trajectories of *known* groups can be compared using covariance structure based methods (e.g., Jöreskog & Sörbom, 1979; McArdle & Epstein, 1987; Meredith & Tisak, 1990) that focus on equality constraints applied to latent means, variances, and shapes to test for the equivalence of these parameters across groups. Likewise, cluster analysis classifies individuals into categories based on the average (i.e., means), scatter (i.e., variances), and shape of the variables used for clustering (Cronbach & Gleser, 1953). Thus, it sorts individuals into groups using the same parameters as covariance structure based methods to compare pre-existing groups. An advantage of cluster analysis is that it can be tailored to classify individuals based on any of the three characteristics of the variables used for the classification process, depending on which of these characteristics are the most relevant from a substantive point of view.

Dynamic cluster analysis has not previously been combined with time series analysis. This combination has the potential to address the limitations of both the nomothetic and idiographic approaches and produce new insights into our understanding of different patterns of change. In this paper, we showcase the use of time series analysis combined with dynamic cluster analysis to detect longitudinal patterns, a process we refer to as ‘time series-based typology’. Specifically, we focus on daily smoking patterns observed after the conclusion of a drastic cigarette reduction program. In the first part of our analyses, we demonstrate the need for differentiating between groups of longitudinal patterns by providing the divergent results of more than 50 time series analyses of daily smoking patterns. We then describe our methodology for grouping these patterns into meaningful clusters. Finally, we identify predictors of these clusters through the use of relevant baseline and follow-up information. This last step serves the dual purpose of establishing the external validity of our identified clusters of growth patterns as well as providing important data (e.g., treatment matching) for future reduction and cessation studies.

Method

Participants

The sample analyzed in this paper is a subset of 151 active smokers recruited for an experimental study to determine the effects of reduced smoking on various biomarkers of carcinogen and other toxicant exposure (Hatsukami et al., 2005; Hecht et al., 2004). The original study consisted of three phases: baseline, reduction, and maintenance. Our study focuses on the 6 week-long maintenance phase. Only 100 participants were retained by the onset of the maintenance phase. Only 57 participants completed daily records for the first 40 days of the maintenance phase (substantially less participants had records for the last two days of the 6-week phase), and are the focus of this study.

Participants were recruited in Minnesota by advertisements in metropolitan and campus newspapers and radio that targeted active cigarette smokers between the ages of 18 and 70 with an interest in reducing cigarette use but not quitting within the next 30 days. Interested individuals were screened to determine whether they met the following inclusion criteria: (a) smoked 15–45 cigarettes per day for the past year; (b) were in apparently good physical health with no unstable medical condition; (c) had no contraindications for nicotine replacement use such as active ulcers, recent heart attack, heart disease or irregular heartbeat, high blood pressure not controlled by medication, or medication use that might affect tobacco use or be affected by reduction of tobacco use; (d) were in good mental health (e.g., not taking psychotropic medications or experiencing psychiatric diagnosis, including substance abuse, as determined by the Diagnostic and Statistical Manual of Mental Disorders, Fourth Edition criteria (American Psychiatric Association, 1994), within the past 6 months); (e) were not using other tobacco or nicotine products; and (f) if female, were not pregnant or nursing. Eligible individuals were given a cash incentive and enrolled in the study.

The sub-sample used in our analyses was predominantly Caucasian (94.7%) and male (52.6%). The ages ranged from 20 to 68 years (M = 47.9, SD = 11.3). Approximately half (49.1%) the sample reported an annual income between $30,000 and $69,000. Of the other half, more participants (38.6%) reported an annual income of less than $30,000. In terms of smoking characteristics, the average daily smoking rate at baseline was 25.7 cigarettes (SD = 7.1). The average total cotinine level (adjusted for urine concentration) was 5041.1 (SD = 2299.1) ng/mL. Participants started smoking on average at 15.6 years of age (SD = 3.6). The sub-sample was representative of the overall sample for all of these variables.

Procedure

Throughout all three phases of the study (baseline, cigarette reduction, and maintenance), participants consistently smoked their own brand and type of cigarette. The baseline phase lasted two weeks during which participants were asked to continue their regular smoking levels. In the reduction phase, participants attempted consecutive two-week step-downs (a % of baseline smoking): (1) weeks 1–2, 25% reduction; (2) weeks 3–4, 50% reduction; and (3) week 5–6, 75% reduction. Finally, the maintenance phase lasted an additional six weeks during which participants attempted to maintain their 75% reduced levels of smoking.

During the reduction and maintenance phases, participants were given nicotine replacement therapy (NRT; i.e., nicotine gum, 4 mg Nicorette® gum and nicotine patch,14/21mg Nicoderm® CQ) supplied by GlaxoSmithKline. During the first step-down (i.e., 25%), all participants used nicotine gum. In the next two step-downs (i.e., 50% and 75%), if participants were not within two cigarettes of their goal, they were offered the option of using a patch (i.e., 14 mg patch for 50% step-down, 21 mg patch for 75% step-down) along with the nicotine gum. After the six-week reduction period, participants who demonstrated some reduction in smoking were advised to sustain or increase their level of smoking reduction to 50% or more of their baseline smoking or to quit smoking. Participants were given NRTs (nicotine gum or patch) for another 6 weeks, with the goal of gradually reducing their use of nicotine gum over this latter 6-week period.

Measures

Measures were taken on three different time schedules: (1) one-time baseline assessment; (2) during seven clinic visits; and (3) daily diary reports.

Participant Characteristics—Self-reported demographic characteristics and smoking-history variables were collected using author-constructed instruments (see Hecht et al., 2004a, 2004b).

Nicotine Dependence—Nicotine dependence was assessed using the Fagerström Tolerance Questionnaire (FTQ: Fagerström, 1978).

Motivation and Self-efficacy—Motivation and self-efficacy to reduce and quit smoking was evaluated using a modified version of the Motivation and Self-Efficacy Scale (Baer & Lichtenstein, 1988). The scale consisted of 8 items that were rated on a 10-point Likert scale ("not at all" to "extremely"), with four items each for smoking reduction (Coefficient Alpha = .85) and smoking cessation (Coefficient Alpha = .93). The four items asked the participants to describe their motivation, confidence, effectiveness of skills, and amount of effort to reduce and quit smoking, respectively. An initial assessment was included as part of the baseline assessment, and repeated measures were taken at subsequent clinic visits.

Tobacco Biomarkers—The following tobacco biomarkers were assessed at baseline: (a) carbon monoxide levels (CO) (measured in parts-per-million (ppm)); and (b) cotinine (measured in ng/mL). Carbon monoxide levels were measured with the Bedfont Micro Smokerlyzer. Cotinine and its glucoronides (total cotinine) were quantified as described elsewhere (Hecht et al., 1999) using 80ml first morning urine voids and calculated per milligram creatinine.

Cigarette Smoking Rate—Participants were asked to record the time of each cigarette they smoked on a daily recording card. Smoking instances were summed per day to provide daily cigarette smoking rates, because the number of cigarettes smoked per day is one of the most commonly used measures used to describe smoking behavior. Furthermore, the self-report of this measure is highly accurate (Velicer, Prochaska, Rossi, & Snow, 1992).

Results

Time Series Analysis

The timeline of cigarettes smoked per day was plotted for each participant, and the series analyzed using time series analysis (e.g., Glass, Willson, & Gottman, 1975; Velicer & Fava, 2003). Time series analysis is a regression-based technique for analyzing sequentially spaced observations. It uses autoregressive integrated moving average (ARIMA) models of order (p, d, q) to model the serial dependence of such data. Three types of terms are estimated. The autoregressive (AR) terms describe the dependency among successive observations. Each AR term has an associated correlation coefficient that describes the magnitude of the dependency. For example, a model with two autoregressive terms ($p = 2$) is one in which an observation is predicted by two previous observations. The moving average (MA) terms describe the persistence of a random shock from one observation to the next. A model with two moving average terms ($q = 2$) is one in which an observation depends on two preceding random shocks. Difference terms describe the number of times a series has to be differenced to make it stationary. Two terms ($d = 2$) implies a series that has to be differenced twice to make it stationary.

The identification of the correct ARIMA model underlying an observed time series has been and continues to be problematic (Velicer & Harrop, 1983). As an alternative, the general transformation approach (Velicer & McDonald, 1984) can be used, which simply uses an ARIMA (5, 0, 0) model (i.e., an autoregressive model of order 5) for all time series. A simulation study has shown that an ARIMA (5, 0, 0) model adequately approximates most commonly encountered time series in the behavioral sciences (Harrop & Velicer, 1985; Velicer & Colby, 2005a, 2005b), and thus we used this approach to model the serial dependence of the 57 time series analyzed in this paper.

In addition to modeling the intercept and serial dependence of the time series, we also estimated a linear trend parameter (i.e., slope) for each time series to estimate changes in daily smoking to give us information about each individual's daily smoking trend. Autoregressive parameters and slope represent the unique parameters defining the longitudinal nature of time series data.

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The mean and error variance parameters were also estimated. Results of the individual time series analyses are presented in Table 1.

On average, the 57 participants started the maintenance phase with a daily smoking rate of 7.85 cigarettes per day. Approximately half of the participants (50.9%) had significant first-order autoregressive parameters, and 17.5% had significant second-order autoregressive parameters. The autoregressive parameters for daily smoking rates were generally positive on average. The first-order autoregressive parameter estimates tended to be larger (M = 0.56, SD = 0.28) than second-order autoregressive parameter estimates (M = 0.03, SD = 0.52). Table 1 includes only the first two autoregressive terms, because the 3rd – 5th autoregressive terms were rarely (5.7% of the cases) significant.

Linear trends were significant for more than half of the sample (59.6%), indicating that there were significant changes in smoking rates over time. Of particular note is the fact that both positive and negative trends were observed. Of the statistically significant slope parameters, the majority were positive (58.8%), indicating an increase in the number of cigarettes smoked per day after the conclusion of the cigarette reduction program. However, a substantial portion of the statistically significant slope parameters were negative (41.2%), pointing towards a diversity of longitudinal patterns underlying the daily smoking patterns of the sample.

Time series-based Typology

The results of the individual time series analyses demonstrated a diversity of autoregressive and linear trend patterns. This diversity suggested that there might be sub-groups within the sample who followed distinctly different patterns of daily smoking rates in the maintenance phase. In order to identify these sub-groups empirically, a time series-based typology was performed to determine if different dynatypes could be identified using each individual’s time series data (i.e., the first 40 recordings of daily smoking rates in the maintenance phase per participant).

Cluster analyses classify units based on the level, scatter, and shape of the variables used for clustering (Cronbach & Gleser, 1953). They are particularly sensitive to differences in level, and much less so to differences in shape (Dumenci & Windle, 2001). In our case, the participants varied dramatically in their levels of daily smoking rate throughout the 40 days of observation (ranging from 0 – 48 cigarettes smoked per day), a factor which would have strongly impacted the cluster analysis classification process. Our main interest in clustering participants, however, was in clustering their longitudinal smoking trajectories by their shape. Furthermore, as mentioned before, the autoregressive patterns of the participants varied considerably. Thus, to prevent both of these factors from impacting the clustering process, we used standardized residuals from the ARIMA (5, 0, 0) model (fitting intercepts, not slopes) for each participant as the input data. That is to say, instead of using the residuals of the time series models listed in Table 1, we used the residuals of time series models that fit the intercept and autoregressive terms, but did not include a linear trend (i.e., slope) parameter, as that was the feature of the data we wanted to capitalize on in the cluster analysis. Standardization in cluster analysis is a typical pre-processing step to avoid unintended weighting. By doing so, we were able to examine the trajectories of the participants’ smoking rates relative to their own maintenance phase starting point, and without the presence of autocorrelation. The resulting cluster analysis used 39 variables (40 observations of daily smoking rates per person minus adjustment based on the first day) to classify 57 participants into clusters.

All analyses were performed using the squared Euclidean distance metric and Ward’s minimum variance algorithm (Ward, 1963). Ward’s algorithm is a hierarchical agglomerative procedure that has been shown to be one of the better clustering methods in several simulation studies (Blashfield, 1976; Milligan, 1980; Milligan & Cooper, 1987; Milligan & Hirtle, 2003; Overall, Gibson, & Novy, 1993). Since hierarchical cluster analyses are generally sensitive to the input order of the data (e.g., Podani, 1997), we used the SPSS add-on PermuCLUSTER (van der Kloot, Spanns, & Heiser, 2005) to compare the cluster solutions obtained from 100 random permutations of the input order. The cluster solutions were identical for all permutations with an overall fit of the normalized sum of the squared differences (SSDif) equal to 59.41. This indicated that no cluster ties were present, and thus the input order of the data did not affect the clustering procedure.

Several methods were used to determine the number of clusters. These included the inverse scree test (Lathrop & Williams, 1987) and the pseudo F test (Calinski & Harabasz, 1974), which were used to narrow the range of cluster solutions that would be interpreted. As a next step, visual inspection of the cluster profiles was performed along with an inspection of the dendogram. Based on these indices, a 3-cluster solution was chosen as being most parsimonious and accurate. Figure 1 plots these three cluster-averages across the first 40 observations of daily smoking in the maintenance phase. To reflect our adjustment for smoking level differences used in the cluster solution, we focused on intra-individual difference scores rather than daily smoking rates. That is, for each participant, we subtracted their initial daily smoking rate (ranging from 2 – 18 cigarettes per day) at the onset of the maintenance phase from subsequent daily smoking rates, permitting examination of the trajectories relative to maintenance phase starting points.

The three clusters were interpreted as representing three distinct types of maintenance patterns: (a) Increasing (47.4%), Constant (12.3%), and Decreasing (40.4%). These descriptive labels correspond well with the slope parameters estimated in the individual time series analyses. Trajectories classified as “Increasing” generally had significant positive slope parameters, trajectories classified as “Constant” had negligible slope parameters, and trajectories classified as “Decreasing” generally had significant negative slope parameters. Table 1 lists the time series analysis results for each participant, grouped by cluster.

External validation

The external validity of the three dynatypes was evaluated in two ways. First, baseline characteristics of the clusters were compared to identify any systematic differences between the groups. Second, smoking related attitudes measured directly at the onset of the maintenance phase were compared between the three groups.

To determine if there were any significant baseline differences between the three dynatypes, we tested a number of demographic (i.e., age, gender, ethnic background, education, and income), psychological (i.e., depression, motivation and self-efficacy), physiological (i.e., body weight, carbon monoxide, cotinine level, and nicotine dependence), and smoking history characteristics (i.e., baseline cigarettes per day, age of smoking initiation, years of smoking, number of 24-hour quit attempts, cut-down history, filter types, and living with smokers) using a series of one-way ANOVAs and chi-square tests. The *p*-values were adjusted for multiple comparisons using the step-down Bonferroni method of Holm (1979). No statistically significant differences were found for any of the variables. Since one of the three clusters (constant smoking rate profile) had a limited sample size, we also compared just the “Increasing” and “Decreasing” clusters to each other. Again, there were no statistically significant differences between the two clusters of smokers at baseline. Means, standard deviations, and percentages for each cluster for all variables used for these analyses are reported in Table 2.

To test for differences between the maintenance patterns immediately before the start of the maintenance phase, we conducted a multivariate analysis of variance (MANOVA) on smoking related attitudes as dependent variables and cluster membership as the independent variable.

The results showed that there were significant differences for the combined dependent variables (i.e., smoking reduction and cessation attitudes) between the identified groups of smokers using Wilks' Lambda criteria ($F(4, 106) = 3.46$, $p = .011$, $\eta^2 = .115$). Significant differences on both univariate ANOVAs with post-hoc Tukey tests were found for both subscales ($F(2, 54) = 6.998$, $p = .002$, $\eta^2 = .206$; $F(2, 54) = 4.714$, $p = .013$, $\eta^2 = .149$). For the Smoking Reduction subscale, participants in the "Decreasing" smoking rate cluster had significantly higher Motivation and Self-efficacy scores than participants in either the "Constant" or "Increasing" smoking rate cluster. For the Smoking Cessation subscale, participants in the "Decreasing" smoking rate cluster only had significantly higher motivation and self-efficacy scores than participants in the "Increasing" smoking rate cluster.

Discussion

This study combined dynamic cluster analysis with time series analysis to investigate the maintenance patterns of daily smoking following drastic cigarette reduction. Our goal was to showcase the use of the time-series based typology as a means of identifying groups of smokers who followed substantively different longitudinal patterns.

To this end, we first demonstrated the need for identifying sub-groups of longitudinal trajectories by considering each participant's daily smoking pattern individually. We investigated each participant's 40 daily recordings through the use of time series analysis. Only a handful of studies have used a time series approach to study smoking behaviors (Emurian, Nellis, Brady, & Ray, 1982; Ray, Emurian, Brady, & Nellis, 1982; Rosel & Elósegui, 1994; Velicer, Redding, Richmond, Greeley, & Swift, 1992). Time series studies in general tend to be based on few if not single individuals, since the number of observations defines the sample size of a time series study, not the number of participants. Previous smoking behavior time series studies were based on 6 to 29 participants. The present study, which is based on 57 participants, represents the largest time series study of smoking behaviors to date. Time series analysis provides estimates of two parameters that are uniquely related to understanding longitudinal change: the autocorrelation patterns that tell us about the processes underlying daily smoking and the slope patterns which tell us about the patterns of change over time. For the most part, autocorrelations in the health and social sciences tend to be positive (Fitzmaurice, Laird, & Ware, 2004). Not surprisingly then, the autocorrelation structures observed in our sample (reported in Table 1) were typically positive, and tended to be restricted to the first order with an average of $\varphi_1 = .55$. In other words, total daily cigarette consumption was relatively strongly related to the previous day's total cigarette consumption in our sample. This finding suggests that there is a smoking set-point, which gets regulated on a daily basis: a regulated set-point, because the return to the set-point is partial, (i.e., $\varphi_1 = .55$); regulated daily, because the autocorrelation structure rarely exceeded an AR1 model. This finding is in agreement with those reported by Rosel and Elósegui (1994), and also in line with the findings by Velicer and colleagues (1992), which was interpreted as evidence supporting the multiple regulation model for nicotine regulation (Leventhal & Cleary, 1980; R. L. Solomon, 1980; R. L. Solomon & Corbit, 1973, 1974). Velicer et al (1992) discuss nicotine regulation models in further detail.[1]

The most striking finding of the individual time series analyses was the diversity of estimated slopes. Most (59.6%) but certainly not all participants exhibited changing cigarette

[1]It should be noted that Velicer and colleagues (1992) focused on semi-daily intervals instead of daily intervals of smoking consumption as done in the present study in order to draw inferences about nicotine regulation models underlying the smoking patterns of number of cigarettes smoked. The time interval they chose (i.e., semi-day) was necessary to study the regulation of nicotine throughout the waking hours of the day. They reported high negative autocorrelations in support of the multiple regulation model for nicotine regulation (Leventhal & Cleary, 1980; R. L. Solomon, 1980; R. L. Solomon & Corbit, 1973, 1974). However, if they had rescored their cigarette consumption rates to reflect a daily pattern, they would have reported a positive autocorrelation pattern, as are reported in this paper.

consumption over the 40 days following the conclusion of the nicotine reduction program. Moreover, the direction and magnitude of the change in the number of cigarettes smoked per day differed widely. Of those participants who did change their daily cigarette consumption, some increased the number of cigarettes smoked per day (58.8%) while others decreased it (41.2%) to varying degrees. This diversity in longitudinal trajectories fueled our motivation to identify subgroups of participants who exhibited meaningfully different smoking behaviors over the 40 days of observation following the conclusion of the cigarette reduction program.

Time series-based Typology

We combined time series analysis with cluster analysis to identify groups of participants who exhibited distinct patterns of daily smoking. The focus of the clustering procedure was the shape or type of trajectory of daily smoking patterns. Thus, through the use of time series analysis, we statistically controlled for individual differences in average smoking levels and autocorrelation structures, so that the cluster procedure was primarily based on the shape of the participants' longitudinal smoking trajectory. Based on this time series based typology, we identified three groups of smokers. The two largest of these groups exhibited dynamic patterns across the 40 days of observation, in which participants either increased (47.4%) or decreased (40.4%) their daily smoking rates over the course of the maintenance phase. The smallest group (12.3%) exhibited stable patterns of daily smoking rates after the end of the cigarette reduction phase.

These three types of smoking patterns following the conclusion of the cigarette reduction program have drastically different implications regarding the participants' success of maintaining the benefit of the harm reduction program. Generally, the goal of interventions is the achievement of sustainable intervention successes. (Note that this was not the goal of the study for which the data were collected.) In this study, only the participants exhibiting stable (i.e., daily stability or weekly stability) smoking patterns (12.3%) achieved this goal. The vast majority (87.7%) of participants did not sustain their level of daily smoking. Instead, they followed a dynamic pattern, one that was either increasing and thereby approaching original levels of daily smoking, or decreasing and thereby approaching quitting. Consequently, our findings suggest that sustaining low rates of smoking is a difficult goal to achieve.

The provocative aspect of our findings is the fact that a nomothetic approach would have reached the opposite conclusion. A nomothetic approach would have rated the success of the drastic cigarette reduction based on the average number of cigarettes smoked across the whole sample. As can be seen in Figure 1, such an approach would have produced a slightly fluctuating but mostly stable pattern of number of cigarettes smoked by the participants during the maintenance phase. What such a pattern fails to communicate is the fact that even though this is the trajectory for the sample at large, it is not the true trajectory of the vast majority of the participants. As we demonstrated through the results of the time-series based typology, most of the participants followed dynamic patterns. And even for the few participants that did exhibit a stable pattern, the relatively smooth nomothetic trend line would be a misrepresentation for some of them, as several of them appear to be externally controlled smokers (Velicer, Redding, Richmond, Greeley, & Swift, 1992), following a weekly cyclical pattern of cigarette consumption rather than a daily regulated pattern.

Predicting Trajectories

Given the finding that sustaining lowered levels of cigarette consumption appears to be a difficult goal to achieve, even for the relatively short span of 40 days, it becomes important to examine the factors which predict the type of trajectory participants' smoking behaviors are likely to take. Such information could be used to improve the maintenance of achieved goals and to target subpopulations that are particularly likely to benefit from additionally intervention efforts.

In our external validity analyses of the three dynatypes we identified, we tested both static predictors of trajectory types, which an intervention would not be able to influence, and dynamic variables, which can and oftentimes are targeted by current interventions. Our results lead us to two important conclusions. First, stable predictors of trajectory type, such as demographic and physiological variables, did not predict daily smoking trajectory type. This observation is of course tempered by the caveat that our external validity analyses (but not any of the previous analyses) were based on small sample sizes with low statistical power. Second, dynamic predictors were important predictors of trajectory type (despite low statistical power), but only when measured at the right time. Baseline predictors did not offer any insight into the type of smoking trajectory participants would exhibit after the drastic cigarette reduction. Assessments of participants' motivation and self-efficacy measured at the conclusion of the cigarette reduction phase, however, did predict trajectory types. These findings support the importance of self-efficacy and motivation in maintaining behavior change. It also underscores the importance of understanding the dynamic interactions of psycho-social variables and behavior change interventions.

Limitations

A major limitation of this study is that it was a secondary data analysis of a data set gathered for another purpose. This limited the variables available for external validity. For example, only two psychosocial measures were included in the original study, and were thus the only ones available for the current analyses. Longer measures, and more psychometrically sound measures of Self-efficacy (Baer & Lichtenstein, 1988, Velicer, DiClemente, Rossi, & Prochaska, (1990) measures would have strengthened our findings. Other psychosocial variables that have been important in other studies, such as Decisional Balance (Velicer, DiClemente, Prochaska, & Brandenberg, 1985) or a variant from other theoretical models and Stage of Change (DiClemente et al., 1991), should be included in any future study.

A second limitation was the limited participant sample size, which both reduced the power of the external validity analyses and prevented an opportunity to split the sample for the time series-based typology. Replication is one important way of establishing internal validity for an exploratory procedure such as cluster analysis. Our limited number of participants precluded such a procedure, and thus more studies are needed to replicate our findings. It should be noted, however, that the sample size limitation did not affect our time series analyses results. The statistical power of time series studies is based on the number of observations per person, not the number of persons. The 40 observations used for our analyses represent a more than adequate sample size for time series analyses (Velicer & Fava, 2003). Furthermore, the results of 57 separate replications in a time series study represents the largest time series smoking study to date.

Lastly, while the procedure we used for identifying subgroups was remarkably sensitive to detecting meaningful differences in the shapes of the smoking rate trajectories, we noted a few idiosyncrasies with this procedure which warrant further attention. For instance, one participant increased his smoking rate for the first 37 days of the maintenance phase and then made a sudden and dramatic drop in the number of cigarettes smoked. The clustering procedure failed to detect this trajectory change and classified the smoker as having an "Increasing" pattern. However, a model error in the time series output alerted us to this participant's peculiar data; a warning the time series-based typology was naturally unable to provide. What is more troublesome, however, is the misclassification of a participant who had no significant slope parameter, a relatively small standard deviation, and a normal model error, but was classified as having a “Decreasing” pattern. Clustering analysis outliers such as these deserve further scrutiny.

Conclusion

Our findings strongly argue for a more pattern-oriented approach in studying longitudinal processes than is currently prevalent in the field. Much can be learned from a focus on empirically identified sub-groups rather than fitting global trajectories to pre-defined groups. Our data demonstrate that the fitting of global trends can be quite misleading. The method we used, a time series-based typology, demonstrated good sensitivity to the identification of meaningfully different trajectories. The groups of smokers we identified through this procedure were meaningfully different, and group membership could be predicted by temporally proximal psychosocial variables, namely Motivation and Self-efficacy. Finally, self-reported Motivation and Self-efficacy appear important prognostic factors for sustained smoking reduction interventions.

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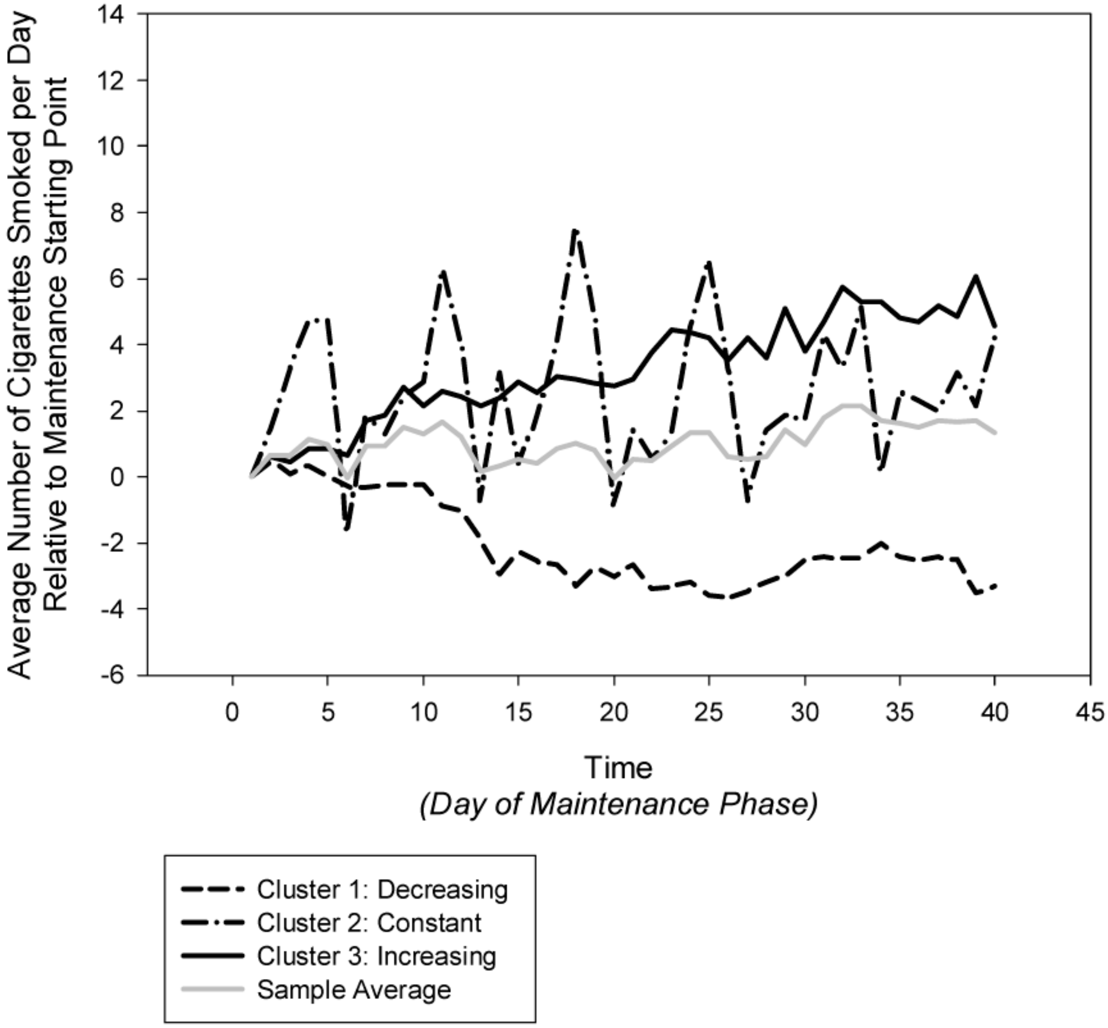

Figure 1.
Daily smoking rate averages of the identified clusters, adjusted for person-specific initial smoking rate in the maintenance phase.

Table 1

Time series analysis results grouped by cluster analysis membership.

Cluster	ID	Descriptives Mean	(SD)	TSA Model Error σ^2	Time series analysis (TSA) parameters Mu	AR1	AR2	Slope
Cluster 1: Increasing smoking rates								
	11	3.35	(2.26)	4.65	2.62*	−0.14	0.08	0.04
	13	0.03	(0.92)	0.62	−0.87*	0.05	−0.10	0.04*
	19	−0.43	(1.48)	2.37	−0.59	0.00	0.01	0.01
	21	3.65	(0.89)	0.82	3.05*	0.17	−0.06	0.03
	27	4.78	(3.01)	1.35	0.09	1.09*a	−0.44	0.22*
	41	4.63	(2.81)	7.59	2.46	0.23	0.38*	0.08
	47	4.23	(2.68)	3.32	0.94	0.42*	−0.30	0.16*
	54	1.10	(1.77)	1.91	−0.86	0.31	−0.24	0.10*
	59	1.20	(1.51)	0.89	−0.80*	0.24	−0.54*	0.10*
	94	10.85	(7.90)	21.22	−0.58	0.33	−0.04	0.58*
	98	2.80	(3.08)	3.12	−1.43*	0.46*	−0.24	0.21*
	101	3.85	(1.70)	0.71	0.69	0.73*	0.24	0.14*
	104	0.65	(1.08)	0.96	0.17	0.54*	−0.37	0.02
	105	−0.93	(3.20)	6.51	−2.79	0.45*	0.18	0.11
	110	2.18	(2.09)	1.11	−0.20	0.60*	0.06	0.11*
	124	8.23	(5.65)	15.06	0.97	0.04	−0.22	0.35*
	125	8.83	(4.51)	14.27	3.70*	0.21	0.21	0.24*
	156	2.88	(2.16)	1.21	−0.43	−0.05	−0.20	0.16*
	168	1.23	(1.48)	2.35	0.96*	0.03	−0.04	0.01
	171	0.95	(1.34)	1.37	−0.14	0.34	0.08	0.05*
	194	2.80	(2.22)	1.76	−0.37	0.43*	−0.31	0.15*
	198	8.95	(5.35)	17.56	1.63	0.49*	0.30	0.24
	201	1.30	(1.14)	0.74	−0.12	0.02	−0.11	0.07*
	231	2.00	(1.13)	1.27	1.81*	0.05	0.19	0.01
	234	3.43	(4.09)	4.43	−1.07	0.43*	0.17	0.25*
	236	1.35	(4.48)	16.70	−1.79	0.13	−0.31	0.15*
	239	3.55	(1.71)	2.11	1.99*	0.20	0.18	0.08*
Cluster 2: Constant smoking rates								
	8	0.18	(2.34)	4.70	−0.08	−0.12	0.03	0.01
	10	12.43	(7.27)	39.76	9.90*	0.06	−0.30	0.13*
	71	0.55	(0.81)	0.40	0.95*	0.55*	−0.38	−0.02*
	89	2.98	(7.01)	41.51	4.37*	−0.47*	−0.53*	−0.07*
	126	1.28	(1.40)	1.73	1.33*	0.45*	−0.18	0.00
	145	0.38	(0.93)	0.64	0.19	−0.21	−0.47*	0.01
	173	0.20	(0.97)	0.95	0.13	0.20	−0.20	0.00
Improving Cluster – Decreasing smoking rate								
	6	−2.63	(3.43)	9.16	−1.62	0.48*	−0.06	−0.03
	25	−5.30	(4.00)	2.54	0.73	0.74*	−0.04	−0.27*
	62	−0.10	(1.39)	1.18	1.43*	−0.21	0.09	−0.07*
	70	0.68	(1.21)	1.41	0.72	0.21	0.23	0.00
	77	−2.15	(4.72)	9.03	−1.21	0.92*	−0.16	−0.09
	85	−3.73	(2.17)	1.42	−0.96	0.37*	0.64*	−0.13*
	88	−1.15	(2.97)	3.78	−0.45	0.67*	0.28	−0.04
	103	−2.70	(2.39)	0.53	0.53	0.59*	0.51*	−0.16*
	107	−0.83	(1.38)	1.68	0.35	0.08	−0.04	−0.06*

Cluster	ID	Descriptives Mean	(SD)	TSA Model Error σ^2	Time series analysis (TSA) parameters Mu	AR1	AR2	Slope
	115	−4.40	(3.87)	7.79	−1.90	0.73*	−0.18	−0.08
	118	−0.60	(0.74)	0.56	−0.28	0.02	−0.12	−0.02
	120	−0.15	(1.97)	3.81	0.47	0.28	0.07	−0.03
	127	−5.48	(2.79)	0.92	0.60	0.68*	0.56*	−0.22*
	152	−2.50	(1.54)	1.09	−1.59*	0.64*	0.27	−0.04
	161	−4.68	(2.34)	0.73	−0.08	0.92*	−0.01	−0.18*
	175	−3.48	(2.11)	0.66	0.37	0.11	0.73*	−0.17
	193	2.48	(1.75)	2.50	2.98*	0.53*	−0.11	−0.03
	195	−5.43	(3.23)	8.44	−2.95*	0.10	−0.05	−0.13*
	202	−1.33	(1.97)	0.71	0.61	0.64*	0.04	−0.10*
	205	−1.18	(1.43)	1.19	−0.22	0.59*	0.23	−0.03
	217	−1.45	(2.56)	3.57	1.57	0.18	0.08	−0.15*
	235	0.23	(0.80)	0.71	0.34	−0.14	−0.14	−0.01
	242	−1.18	(1.26)	0.22	0.65*	1.01*[a]	−0.26	−0.09*

Note: “Cluster” denotes the cluster ID number each participant’s time series is a member of, “ID” denotes the participants’ unique ID numbers, “Descriptives” list the means and standard deviations of the observed time series after subtracting each participant’s number of cigarettes smoked on the first day of the maintenance phase from all subsequent observations, “TSA Model” lists a summary fit index (i.e., the error variance) of each time series model, “Time Series analysis (TSA) parameters” list specific parameter estimates of each fitted TSA model (specifically, the intercept (MU), autoregressive terms 1 and 2 (AR1, AR2) and the linear trend (slope) parameters are displayed)

* marks parameters significant at the .05 level

[a] It should be noted the bounds of stationarity for models of a higher order than AR1 have more complex requirements, which do not necessitate that $-1 < \varphi_1 < 1$ (Yaffee & McGee, 2000).

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Table 2

Baseline characteristics by maintenance pattern group.

Baseline Characteristics	Increasing (n=13) Mean (SD) (column) %	Constant (n=23) Mean (SD) (column) %	Decreasing (n=15) Mean (SD) (column) %
Demographics			
Age	50.22 (9.35)	40.71 (15.42)	47.26 (11.45)
Gender (female)	55.6%	42.9%	39.1%
Ethnicity (white)	92.6%	100.0%	95.7%
Education (3 levels) [a]			
High School or less	33.3%	0.0%	34.8%
Some college	33.3%	57.1%	43.5%
College or more	33.3%	42.9%	21.7%
Income (3 levels)			
$29,000 or less	33.3%	42.9%	43.5%
$30,000 - $69,999	55.6%	28.6%	47.8%
$70,000 ore more	11.1%	28.6%	8.7%
Physiological characteristics			
Weight (in lbs)	168.60 (38.82)	157.20 (26.14)	199.64 (38.82)
CO (in ppm)	22.81 (9.19)	14.93 (5.01)	20.54 (7.87)
Cotinine (ng/mL)*10^{-2}	4.62 (2.12)	4.32 (2.42)	5.76 (2.37)
Nicotine Dependence	5.78 (1.45)	4.57 (1.27)	6.00 (1.38)
Psychological characteristics			
Depression (CES-D)[c]	16.35 (6.39)	15.67 (4.37)	13.95 (4.15)
MSS Score - Reduction	7.02 (1.76)	6.68 (1.67)	7.65 (1.43)
MSS Score - Cessation	5.13 (2.44)	4.50 (2.32)	6.27 (2.47)
Smoking History			
Cigarettes per Day [a]	25.70 (7.45)	20.00 (0.00)	27.13 (7.02)
Age of First Smoking [a]	15.93 (3.08)	15.67 (4.23)	15.17 (4.02)
Years of Smoking [b]	19.92 (11.87)	16.83 (15.80)	15.48 (11.39)
24hr Quit (never)	25.9%	0.0%	22.7%
Cutdown History (never)[a]	33.3%	0.0%	34.8%
Filter type ((ultra)lights) [a]	74.1%	83.3%	43.5%
Living w/ Smokers (yes)	40.7%	33.3%	56.5%

[a]Note: Missing for n=1

[b]Note: missing for n=3

[c]Note: missing for n=8

Table 3

Means and standard deviations of MSS reduction and cessation scores for the three clusters.

Smoking Rate Cluster	MSS Reduction		MSS Cessation	
	Mean	(SD)	Mean	(SD)
Increasing (*n*=13)	8.42	(1.14)	7.23	(2.15)
Constant (*n*=23)	6.25	(2.74)	5.04	(3.04)
Decreasing (*n*=15)	6.78	(1.91)	5.08	(2.83)

Note: MSS Reduction = Motivation and Self-efficacy subscale score for smoking reduction; MSS Cessation = Motivation and Self-efficacy subscale score for smoking cessation