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RESEARCH BRIEF

Applying Publicly Available Contextual Factors to Predict Smoking Relapse in a National Sample

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ABSTRACT

Background: The ecological fallacy is broadly understood, though its complimentary problem, the individualistic or atomistic fallacy, is less often considered. Multilevel models offer the statistical tools needed to avoid both errors by allowing simultaneous consideration of individual, contextual, and policy factors. This study applies such methods to smoking cessation data. Tobacco control is of particular concern in Ohio where the adult smoking prevalence remains around 22%.

Methods: Data from the 1,785 participants in the Technology Enhanced Quitline Study were used to test the theory that contextual factors impact relapse rates and program effectiveness, employing a mixed-effects model to account for the nested nature of the data while testing for the relationship between contextual factors and relapse, controlling for individual characteristics.

Results: No contextual factors or policy variables were significant predictors of smoking relapse in the sample, nor were any associated with the success of the intervention.

Conclusions: While this work could not identify specific influences of contextual and policy factors on smoking outcomes in our sample, it demonstrates the feasibility of adding such predictors to future clinical trials. This project clearly does not rule out the possibility that contextual and policy factors may influence smoking even after controlling for individual characteristics, but does not provide strong evidence of such a link. It is possible that these negative findings may be due to geocoded mailing addresses being a poor proxy for relevant contextual factors, use of the wrong geographic unit of analysis (modifiable areal unit problem), or a lack of temporal resolution in contextual variables.

Key words: Tobacco cessation, multilevel modeling, contextual factors

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INTRODUCTION

For decades, researchers have been wary of the ecological fallacy, wherein aggregate results are assumed to apply to individuals.[1] There is increasing recognition that the opposite error, the individualistic or atomistic fallacy, may equally bias results.[2] Examining only individual factors and ignoring contextual ones gives an incomplete understanding. Multilevel models are statistical methods allowing simultaneous examination of individual and contextual factors.[3]

Despite a strong theoretical basis for examining contextual factors, few trials do so. Smoking cessation trials provide an example of this phenomenon. A PubMed search for clinical trials related to smoking or tobacco cessation, conducted by the authors in December 2018, returned nearly five thousand hits, yet only 64 abstracts (1.3%) included terms related to contextual factors or methods ("contextual," "multilevel," "multi-level," or "neighborhood"). Though the percentage of trials exploring these questions has increased in recent years (2.1% past 10 years, 2.4% past 5 years), numbers remain small. This study explores the feasibility and utility of adding publicly available contextual data to the analysis of an existing tobacco cessation trial.

Numerous studies have identified individual level relapse predictors including substance abuse (e.g., use of other tobacco products, alcohol);[4–6] demographic factors (e.g., age of smoking at relapse);[7,8] psychological factors (e.g., depression, motivation to quit);[5,9–12] and smoking characteristics (e.g., cigarettes per day, time to first cigarette).[7,8,12,13]

A growing body of literature has explored how contextual factors influence smoking rates at the population level. Neighborhood characteristics (e.g., poverty, density of tobacco outlets) and tobacco policies have been associated with smoking prevalence.[14–21] Policies influencing smoking initiation rates include the use of plain packaging and/or prominent, graphic warning labels on cigarettes, increased price of cigarettes through taxation, and institution of smoke-free policies.[22]

This study examined whether publicly available data on contextual- and policy-level factors are associated with individual level smoking relapse, controlling for individual characteristics. Contextual variables were selected based on a review of the smoking literature. The impact of contextual factors on intervention outcomes was also examined by exploring the significance of interaction effects. Multilevel modeling was used to test the theory that contextual factors impact relapse rates and program effectiveness.[23]

METHODS

Setting

This study was a secondary analysis of data from a clinical trial, Technology Enhanced Quitline (TEQ) Study,[24] supplemented by publicly available contextual data. The original study was conducted in collaboration with tobacco quitline operator Alere Wellbeing, Inc (AWI).

Participants

Participants were recruited from 19 AWI client businesses. Individuals employed by these businesses who voluntarily utilized quitline benefits through their employer or health plan benefits package were invited to join the study upon reporting at least 24 hours of abstinence following their quit date. To be eligible, they needed to be English-speaking adults with access to a touch-tone phone. AWI's services are utilized by organizations with a national reach, yielding a geographically diverse sample. As participants were recruited through AWI clients, all were either employed by those clients or dependents of such employees.

Design

Detailed information about the study design has been previously reported.[24] Briefly, the TEQ Study was a randomized trial testing the efficacy of an automated telephone intervention to improve quit success among users of tobacco quitlines.

Upon enrollment, participants were randomized to either: standard quitline treatment, a low intensity intervention (standard treatment plus 10 automated check-ins), or an intensive intervention (standard treatment plus 20 automated check-ins).

Measures

TEQ participants reported demographics, psychological characteristics (i.e., depression, motivation to quit), smoking characteristics (i.e., cigarettes per day, time to first cigarette), past quit attempts, and social network smoking (i.e., exposure to smoking at home and work) at baseline. They were assessed for smoking status at 6- and 12-months post intervention. Participants who reported smoking even a puff during the past 7 and 30 days were defined as having relapsed.

Contextual factors, gathered at the county level, were collected from publicly available data sets. Demographics were drawn from the Robert Wood Johnson Foundation's County Health Rankings Database.[25] Tobacco production, tobacco outlet density, and community demographic data were derived from government sources like the USDA's National Agricultural Statistics Service and US Census.[26,27] Tobacco policies, tobacco taxation, and cessation and prevention spending information were gathered from resources released by advocacy groups including Americans for Nonsmokers Rights publications[28] and Campaign for Tobacco Free Kids,[29–32] supplemented by government website data.[33]

Procedures

The investigators used standard address matching procedures in ArcGIS 10.2 (ESRI, Redlands, CA) to assign each individual to specific geographic coordinates using the participant's residential address. These coordinates were used to link the participant to contextual and policy level factors using geographic information system overlay procedures.

Procedures were approved by Institutional Review Boards at Indiana University and Bluffton University. All participants enrolling in the original study provided verbal informed consent and authorization for the TEQ investigators to use protected health information.

Statistical Analysis

A mixed-effects model was used to account for the nested nature of the data (individuals nested within counties). Given the binary nature of the outcome (i.e., relapse or no relapse) a binomial error distribution and a logit link function was used to produce a generalization of a logistic regression model. Models were fit using the SAS® GLIMMIX procedure (SAS Institute, Cary, NC).

The primary aim was to determine if contextual factors were associated with smoking relapse while controlling for individual-level effects. The significance of adding contextual factors one-at-a-time to a base model containing all individual factors and treatment status was tested. A cutpoint of $\alpha=0.05$ was used to determine significance of adding each variable. A second aim examined whether the effect of the intervention varied based on the context in which it was implemented. This was done by testing the significance of a contextual factor-by-intervention interaction term in a base model including all individual factors, intervention group, and a main effect for the contextual factor. A cutpoint of $\alpha=0.05$ was also used to determine significance of interaction effects.

Multiple imputation was utilized to account for missing data,[34] as this approach theoretically provides less biased estimates.[35] Values for missing data both for predictors and outcome variables were estimated using existing data.[35] This process was repeated ten times, and cumulative results summarized with SAS PROC MI-ANALYZE.[36] Sensitivity analyses were conducted using two alternative methods for dealing with missing data: a respondents-only analysis (assuming information is missing completely at random) and "traditional penalized imputation" in which non-responders to data collection are considered relapsed.[37] The primary analysis using multiple imputation has slightly greater power because, like penalized imputation (missing=smoking), it uses all persons with baseline data but, compared to penalized imputation, it uses more information and produces results with greater power, less bias, and greater accuracy than penalized imputation or responder-only analysis.[35,37]

RESULTS

The TEQ sample included 1,785 participants from 47 states and the District of Columbia (Figure 1). Alaska, Hawaii, and Wyoming had no participants. Participation rates elsewhere ranged from around 0.1 per 100,000 population in Rhode Island to 3.4 per 100,000 population in Minnesota.

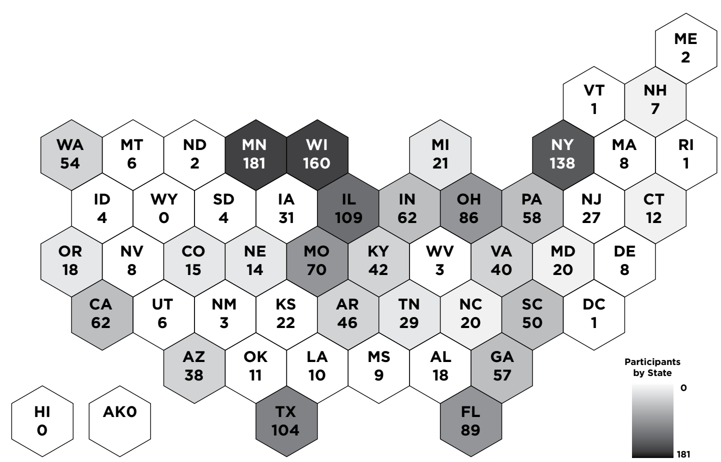

Figure 1. Number of Technology Enhanced Quitline (TEQ) Study participants by state.

Relapse rates at 6 and 12 months ranged from 32-44% depending on the treatment exposure, time point, and outcome measure. Prior to the addition of contextual factors, age, motivation to quit, depression, cigarettes per day, and social network smoking were significant predictors of relapse.[24] Table 1 displays odds ratios for relapse (smoking even one puff) for both 7- and 30-day periods prior to each follow-up interview (6- and 12-months). No contextual factors or policy variables were significant predictors at either time point.

Table 1. Adjusted odds ratios (95% Confidence Interval) describing the change in risk of relapse per change in contextual factor* in a geographically diverse sample of United States smokers attempting to quit.

	6-month survey outcomes		12-month survey outcomes	
Contextual and Policy Factors	Smoked in last 7 days	Smoked in last 30 days	Smoked in last 7 days	Smoked in last 30 days
Unemployment[25] Per 5% increase	1.11 (0.84, 1.46)	1.01 (0.73, 1.38)	1.19 (0.91, 1.56)	1.09 (0.81, 1.47)
Clean indoor air legislation[28] Comprehensive vs. no comprehensive ban	1.13 (0.88, 1.46)	1.08 (0.83, 1.40)	1.05 (0.82, 1.35)	1.12 (0.88, 1.41)
Tobacco tax rate[29-31,33] Per $1 increase	1.08 (0.97, 1.20)	1.04 (0.94, 1.16)	1.02 (0.92, 1.13)	1.00 (0.90, 1.11)
Violent crime rate[25] Per 100 crimes/100,000 people increase	1.02 (0.97, 1.06)	1.01 (0.97, 1.06)	1.01 (0.96, 1.06)	1.01 (0.97, 1.06)
Tobacco production[26] Tobacco producer vs. non-producer	0.81 (0.56, 1.18)	1.03 (0.72, 1.49)	0.90 (0.61, 1.31)	0.97 (0.69, 1.36)
Smoking prevalence[25] Per 5% increase	0.94 (0.84, 1.05)	0.99 (0.89, 1.10)	0.94 (0.84, 1.06)	0.99 (0.88, 1.10)
Tobacco retailer density[27] Per 1 outlet/1000 population increase	0.92 (0.61, 1.40)	0.96 (0.64, 1.46)	1.10 (0.77, 1.59)	1.18 (0.82, 1.68)
Tobacco control funding[32] Per 25% of CDC target increase	0.96 (0.73, 1.25)	0.93 (0.73, 1.19)	0.98 (0.77, 1.23)	1.02 (0.79, 1.32)

*Controlling for individuals' age, sex, race, ethnicity, education, cigarettes per day, time to first cigarette, number of quit prior attempts, duration of longest quit attempt, motivation, depression, social network smoking, and treatment status.

Sensitivity analyses examining the impact of alternative ways of addressing missing data yielded similar results, with one exception. When limiting analyses to respondents without missing data (respondent-only analysis), significant effects were observed for presence of a comprehensive clean indoor air policy and increasing tobacco tax rates at the 6-month follow-up. Unexpectedly, odds ratios for both factors were greater than 1, indicating an increased likelihood of relapse for individuals in regions with comprehensive clean indoor air policies and higher tobacco tax rates. However, no contextual factors were significant when conducting a traditional penalized imputation analysis (missing = relapsed). No significant interactions, indicating contextual impacts on intervention effectiveness, were observed.

DISCUSSION

This study did not find a significant relationship between policy or contextual factors and smoking relapse. Sensitivity analyses were generally consistent with the main analyses using multiple imputation. Although respondent-only analysis revealed two contextual findings, research has shown that such results are generally biased and less trustworthy compared to the multiple imputation results. While this project has some suggestive findings, and clearly does not rule out the possibility that contextual and policy factors may influence smoking, it does not provide strong evidence of such a link. In considering these negative findings, several possibilities apart from a lack of effect should be considered.

First, geocoded mailing addresses may be a poor proxy for the contextual factors most relevant to individuals. This has been termed the uncertain geographic context problem.[38] Individuals work, play, worship, shop, and carry on many other activities outside the home. Exposures in these areas may be more important than those in the home context. As the sample is composed solely of individuals with insurance provided through an employer or health plan, this effect may be more pronounced, as a majority of participants work outside their homes. Additionally, we lack information on residential duration, so individuals may have recently moved to or from the utilized address.

The modifiable areal unit problem presents an additional challenge.[39] When utilizing geographic data, it is difficult to know the correct geographical unit of analysis. Is someone defined by their block group, census tract, zip code, or county? Such questions have not been definitively answered. In this preliminary research, the unit of analysis was often constrained by the availability of data. Where available public data made it possible, we compared the results using measures at several levels (including block group, county, and state). These analyses yielded similar results, though this is an area meriting further exploration.

Temporal factors may have contributed to the negative findings. Contextual data is generally gathered in cross-sectional snapshots, often at one-year intervals. We used data gathered during the study period; however, it is possible that certain contextual factors may have shifted shortly before or after a participant's involvement in the study. An additional consideration is whether changes in contextual factors might be as important as or more important than specific values. For example, a newly imposed smoking ban may be better (or more poorly) enforced than an established ban, or a recent increase in cigarette taxes may initially seem more onerous then it does after a period of adaptation. Incorporating information about the timing of policy implementation may reveal relationships that are masked by cross-sectional measures.

PUBLIC HEALTH IMPLICATIONS

Smoking remains a vital health issue in the state of Ohio. Nationally, adult smoking prevalence has declined steadily from more than 40% to 14% since the mid-1960s.[40] Rates have generally declined in Ohio as well; however, gains have stagnated in recent years, with the smoking prevalence in the state remaining around 22% since 2014,[41] leaving Ohio with the sixth highest smoking rate in the United States.[42] Better understanding the impact of contextual factors on smoking relapse could play a vital role in targeting interventions and shaping healthier communities.

This project tested the hypothesis that contextual and policy factors captured by publicly available data sets would measurably impact the risk of relapse, even after controlling for individual characteristics; however, the current study did not find such factors to add significant predictive power among a national sample of corporate quitline clients in a clinical trial. Technical and theoretical developments have ushered in an era of "big data." The increasing ease with which contextual data may be captured, stored, shared, and analyzed will allow for further examinations of the impact of contextual factors on smoking and other public health outcomes. While this work could not identify specific influences of contextual and policy factors on smoking outcomes in our sample, it demonstrates the feasibility of merging publicly available contextual data into future clinical trials to further explore the role of policy and environment on smoking and other health behaviors.

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REFERENCES

1. Robinson, W. S. Ecological Correlations and the Behavior of Individuals. American Sociological Review 15, 351–357 (1950).
2. Subramanian, S. V., Jones, K., Kaddour, A. & Krieger, N. Revisiting Robinson: the perils of individualistic and ecologic fallacy. Int J Epidemiol 38, 342–360; author reply 370-373 (2009).
3. Duncan, C., Jones, K. & Moon, G. Context, composition and heterogeneity: using multilevel models in health research. Soc Sci Med 46, 97–117 (1998).
4. Krall, E. A., Garvey, A. J. & Garcia, R. I. Smoking relapse after 2 years of abstinence: findings from the VA Normative Aging Study. Nicotine Tob. Res. 4, 95–100 (2002).
5. VanderVeen, J. W. et al. Differences in drinking patterns, occupational stress, and exposure to potentially traumatic events among firefighters: predictors of smoking relapse. Am J Addict 21, 550–554 (2012).
6. Garvey, A. J., Bliss, R. E., Hitchcock, J. L., Heinold, J. W. & Rosner, B. Predictors of smoking relapse among self-quitters: a report from the Normative Aging Study. Addict Behav 17, 367–377 (1992).
7. Japuntich, S. J. et al. Smoker characteristics and smoking-cessation milestones. Am J Prev Med 40, 286–294 (2011).
8. Hawkins, J., Hollingworth, W. & Campbell, R. Long-term smoking relapse: a study using the british household panel survey. Nicotine Tob. Res. 12, 1228–1235 (2010).
9. Gökbayrak, N. S., Paiva, A. L., Blissmer, B. J. & Prochaska, J. O. Predictors of relapse among smokers: transtheoretical effort variables, demographics, and smoking severity. Addict Behav 42, 176–179 (2015).
10. López-Torrecillas, F., Perales, J. C., Nieto-Ruiz, A. & Verdejo-García, A. Temperament and impulsivity predictors of smoking cessation outcomes. PLoS ONE 9, e112440 (2014).
11. Nakajima, M. & al'Absi, M. Predictors of risk for smoking relapse in men and women: a prospective examination. Psychol Addict Behav 26, 633–637 (2012).
12. Herd, N., Borland, R. & Hyland, A. Predictors of smoking relapse by duration of abstinence: findings from the International Tobacco Control (ITC) Four Country Survey. Addiction 104, 2088–2099 (2009).
13. Mueller, E. T. et al. Delay of smoking gratification as a laboratory model of relapse: effects of incentives for not smoking, and relationship with measures of executive function. Behav Pharmacol 20, 461–473 (2009).
14. Verdonk-Kleinjan, W. M. I., Candel, M. J. J. M., Knibbe, R. A., Willemsen, M. C. & de Vries, H. Effects of a workplace-smoking ban in combination with tax increases on smoking in the Dutch population. Nicotine Tob. Res. 13, 412–418 (2011).
15. Finney Rutten, L. J., Augustson, E. M., Moser, R. P., Beckjord, E. B. & Hesse, B. W. Smoking knowledge and behavior in the United States: sociodemographic, smoking status, and geographic patterns. Nicotine Tob. Res. 10, 1559–1570 (2008).
16. Datta, G. D. et al. Individual, neighborhood, and state-level predictors of smoking among US Black women: a multilevel analysis. Soc Sci Med 63, 1034–1044 (2006).
17. Bauer, J. E., Hyland, A., Li, Q., Steger, C. & Cummings, K. M. A longitudinal assessment of the impact of smoke-free worksite policies on tobacco use. Am J Public Health 95, 1024–1029 (2005).
18. Frieden, T. R. et al. Adult tobacco use levels after intensive tobacco control measures: New York City, 2002-2003. Am J Public Health 95, 1016–1023 (2005).
19. Diez Roux, A. V., Merkin, S. S., Hannan, P., Jacobs, D. R. & Kiefe, C. I. Area characteristics, individual-level socioeconomic indicators, and smoking in young adults: the coronary artery disease risk development in young adults study. Am J Epidemiol 157, 315–326 (2003).
20. Fichtenberg, C. M. & Glantz, S. A. Effect of smoke-free workplaces on smoking behaviour: systematic review. BMJ 325, 188 (2002).
21. Brownson, R. C., Hopkins, D. P. & Wakefield, M. A. Effects of smoking restrictions in the workplace. Annu Rev Public Health 23, 333–348 (2002).
22. Pierce, J. P., White, V. M. & Emery, S. L. What public health strategies are needed to reduce smoking initiation? Tob Control 21, 258–264 (2012).
23. Warnecke, R. B. et al. Approaching health disparities from a population perspective: the National Institutes of Health Centers for Population Health and Health Disparities. Am J Public Health 98, 1608–1615 (2008).
24. McDaniel, A. M. et al. A randomised controlled trial to prevent smoking relapse among recently quit smokers enrolled in employer and health plan sponsored quitlines. BMJ Open 5, e007260 (2015).
25. Robert Wood Johnson Foundation. County Health Rankings. County Health Rankings & Roadmaps Available at: http://www.countyhealthrankings.org/. (Accessed: 14th December 2018)
26. United States Department of Agriculture. National Agricultural Statistics Service. Available at: https://www.nass.usda.gov/. (Accessed: 14th December 2018)
27. United States Census Bureau. Census.gov. Available at: https://www.census.gov/en.html. (Accessed: 14th December 2018)
28. Americans for Nonsmokers' Rights. Smokefree Lists, Maps, and Data. no-smoke.org Available at: http://www.no-smoke.org/goingsmokefree.php?id=519#ords. (Accessed: 20th March 2013)
29. Boonn, A. State cigarette excise tax rates & rankings. Campaign for Tobacco-Free Kids (2011). Available at: https://www.tobaccofreekids.org/research/factsheets/pdf/0097.pdf. (Accessed: 15th September 2013)
30. Boonn, A. Top combined state-local cigarette tax rates. Campaign for Tobacco-Free Kids (2011). Available at: https://www.tobaccofreekids.org/research/factsheets/pdf/0267.pdf. (Accessed: 15th September 2013)
31. Boonn, A. Local government cigarette tax rates & fees. Campaign for Tobacco-Free Kids (2011). Available at: https://www.tobaccofreekids.org/research/factsheets/pdf/0304.pdf. (Accessed: 15th September 2013)
32. Campaign for Tobacco-Free Kids et al. Broken promises to our children: The 1998 state tobacco settlement 14 years later. (Campaign for Tobacco-Free Kids, 2012).
33. Alabama Department of Revenue. Current tobacco tax rates report. (2013). Available at: http://revenue.alabama.gov/tobaccotax/t_report.pdf. (Accessed: 20th September 2013) NOTE: Site no longer active. Equivalent current data available at: https://revenue.alabama.gov/wp-content/uploads/2017/09/t_report.pdf. (Accessed: 9th May 2019)
34. Raghunathan, T. E., Lepkowski, J. M., Van Hoewyk, J. & Solenberger, P. A multivariate technique for multiply imputing missing values using a sequence of regression models. Surv Methodol 27, 85–96 (2001).
35. Asparouhov, T. & Muthén, B. Multiple imputation with Mplus. MPlus Web Notes (2010).
36. SAS Institute Inc. The MIANALYZE Procedure. in SAS/STAT® 13.1 User's Guide 5172–5231 (SAS Institute Inc., 2013).
37. Blankers, M. et al. The Missing=Smoking Assumption: A Fallacy in Internet-Based Smoking Cessation Trials? Nicotine Tob Res (2015). doi:10.1093/ntr/ntv055
38. Kwan, M.-P. The uncertain geographic context problem. Ann Assoc Am Geogr 102, 958–968 (2012).
39. Openshaw, S. & Taylor, P. J. A million or so correlation coefficients: three experiments on the modifiable areal unit problem. Statistical applications in the spatial sciences 21, 127–144 (1979).

40. Wang, T. W. Tobacco Product Use Among Adults — United States, 2017. MMWR Morb Mortal Wkly Rep 67, (2018).

41. Ohio Department of Health. Tobacco Data and Statistics. (2018). Available at: https://odh.ohio.gov/wps/portal/gov/odh/know-our-programs/tobacco-use-prevention-and-cessation/data/. (Accessed: 15th December 2018)

42. Centers for Disease Control and Prevention. Map of Cigarette Use Among Adults. STATE System (2017). Available at: https://www.cdc.gov/statesystem/cigaretteuseadult.html. (Accessed: 15th December 2018)