ABSTRACT

Advances in behavioural economics have begun to provide a new toolkit of theories, models, and empirical methods for designing and evaluating policy. While many of these techniques are highly relevant to behavioral problems that planners encounter when consulting the public, crafting policy and regulations, and promoting sustainable patterns of behavior, this approach has received only limited attention in the planning and transportation literature. I review this literature and present a framework for generating, implementing, and testing the results of different interventions designed to affect users’ travel behavior by delivering behavioral feedback via an activity-tracking smartphone application. The results of this promotional strategy are tested in two pilot projects among university students and “Bike to Work Week” participants in British Columbia and Minnesota. I also present further tools for conducting such experiments and additional experimental designs relevant to testing these hypotheses. Implications for program evaluation, planning practice, and transportation research are discussed.
PREFACE

Chapters 3 and 4: A version of Chapters 3 and 4 have been submitted for presentation as Zhao, J. and Baird, T. “‘Nudging’ Active Travel: A Framework for Behavioral Interventions Using Mobile Technology.” All major concept formation, experimental design, and data collection and analysis, as well as the composition of the manuscript, are my original work. J. Zhao was the supervisory author on this project and was involved throughout the project on concept formation and manuscript edits. The fieldwork reported in Chapter 4 was covered by UBC Ethics Certificate number H13-00218.

Chapter 6: A version of Chapter 6 has been submitted for publication as Welsh, B., Baird, T., Zhao, J., and Block-Schachter, D. “A Web App Design to Implement Travel Behavior Nudging Using ‘Moves.’” The system was conceived and designed by B. Welsh and I, and implemented by B. Welsh. The manuscript was written by B. Welsh and I. J. Zhao was the supervisory author on this project and was involved throughout the project on concept formation and manuscript edits. D. Block-Schachter provided additional manuscript edits.
TABLE OF CONTENTS

ABSTRACT.................................................................................................................................................. ii
PREFACE.................................................................................................................................................... iii
TABLE OF CONTENTS............................................................................................................................. iv
LIST OF TABLES..................................................................................................................................... viii
LIST OF FIGURES.................................................................................................................................... ix
ACKNOWLEDGEMENTS.......................................................................................................................... x
1. INTRODUCTION .................................................................................................................................... 1
   1.1 Introduction: Applying Behavioral Findings to Transportation Planning .......................................... 1
   1.2 Challenges for Transportation Planners.............................................................................................. 3
   1.3 Objectives and Methodology .............................................................................................................. 4
      1.3.1 Objectives .................................................................................................................................... 4
      1.3.2 Methodology ................................................................................................................................ 5
   1.4 Outline................................................................................................................................................. 6
2. A BRIEF INTRODUCTION TO BEHAVIORAL ECONOMICS .......................................................... 8
   2.1 Introduction: The History, Findings, and Applications of Behavioral Economics ............................. 8
   2.2. A Short History of Psychology and Economics ................................................................................. 8
   2.3. Core Findings of Behavioral Economics .......................................................................................... 14
      2.3.1 The Methodology of Behavioral Economics ............................................................................. 14
      2.3.2 Heuristics and Biases ................................................................................................................. 17
      2.3.3 Fairness, Cooperation, and Altruism.......................................................................................... 22
      2.3.4 Mental Accounting of Consumption, Spending, Investments, and Losses ............................ 25
      2.3.5 Bounded and Ecological Rationality......................................................................................... 28
   2.4 Applications of Behavioral Economics in Planning ......................................................................... 30
      2.4.1 A Framework for Practitioners .................................................................................................. 31
      2.4.2 Transportation Pricing and Mental Accounting.......................................................................... 33
5.2 Behavioral Research ........................................................................................................................ 75
5.3 Design Parameters ............................................................................................................................ 77
5.4 Web App Design ............................................................................................................................... 79
  5.4.1 Overview .................................................................................................................................... 79
  5.4.2 User Perspective ......................................................................................................................... 82
  5.4.3 Data Flow ................................................................................................................................... 86
  5.4.4 Researcher Perspective .............................................................................................................. 89
  5.4.5 Implementation .......................................................................................................................... 91
5.5 Discussion ......................................................................................................................................... 91
  5.5.1 Desired Features ......................................................................................................................... 91
  5.5.2 Future Applications .................................................................................................................... 92
5.6 Conclusion ........................................................................................................................................ 93

6. FURTHER EXPERIMENTAL DESIGNS ............................................................................................. 95
6.1 Introduction ....................................................................................................................................... 95
6.2 Mechanical Turk Study ..................................................................................................................... 96
  2.1 Recruitment Using Amazon Mechanical Turk ............................................................................. 96
  6.2.2 Experimental Design and Interventions ..................................................................................... 98
  6.2.3 Data ............................................................................................................................................ 98
6.3 Fall 2013 Bike Walk Week Study ................................................................................................... 101
  6.3.1 Recruitment Using Social Media ............................................................................................. 101
  6.3.2 Experimental Design ................................................................................................................ 103
  6.3.3 Data .......................................................................................................................................... 103
6.4 Research Goals and Discussion ...................................................................................................... 105

7. CONCLUSION ..................................................................................................................................... 107
7.1 Key Findings ................................................................................................................................... 107
  7.1.1 The Potential of Behavioral Economics to Enhance Transportation Models and Interventions
  .......................................................................................................................................................... 107
7.1.2 Approaches to Behavioral Design of Travel Information .................................................. 107

7.1.3 Lessons for Research Partnerships with Active Travel Advocates .................................. 107

7.1.4 Viability of Commercial Activity Tracking Apps for Travel Data Collection .................. 108

7.2 Limitations .................................................................................................................................. 109

7.3 Implications ................................................................................................................................... 111

7.4 Future Research ............................................................................................................................... 114

7.4.1 Broader Samples and Travel Surveys ..................................................................................... 114

7.4.2 Combining Activity Tracking and Other Data Sources ......................................................... 116

7.4.3 Program and Infrastructure Evaluation ................................................................................... 116

7.4.4 Verification and Enforcement of Incentive Programs ............................................................ 117

7.4.5 Open Data Access and Visualization ....................................................................................... 118

BIBLIOGRAPHY .............................................................................................................................. 119

APPENDIX: SAMPLE QUESTIONNAIRES ..................................................................................... 130

I. Pre-Study Questionnaire .................................................................................................................. 130

II. Post-Study Questionnaire .............................................................................................................. 135
LIST OF TABLES

Table 1: Comparison of Experiments ......................................................................................................... 58
Table 2: Study 1 Attrition Sources.............................................................................................................. 63
Table 3: Study 2 Attrition Sources (Twin Cities participants only).......................................................... 68
Table 4: Study 2 ANOVA Results.............................................................................................................. 70
Table 5: Active Commuting Behaviors ...................................................................................................... 71
Table 6: Comparison of Experiments ......................................................................................................... 96
# LIST OF FIGURES

<table>
<thead>
<tr>
<th>Figure</th>
<th>Description</th>
<th>Page</th>
</tr>
</thead>
<tbody>
<tr>
<td>Figure 1</td>
<td>Example Feedback Report</td>
<td>62</td>
</tr>
<tr>
<td>Figure 2</td>
<td>Study 1 Activity Totals</td>
<td>65</td>
</tr>
<tr>
<td>Figure 3</td>
<td>Interactions Between System Components</td>
<td>81</td>
</tr>
<tr>
<td>Figure 4</td>
<td>Sign-up Process Flowchart</td>
<td>85</td>
</tr>
<tr>
<td>Figure 5</td>
<td>Sign-up Data Flow</td>
<td>87</td>
</tr>
<tr>
<td>Figure 6</td>
<td>Data Flow for Ongoing Collection</td>
<td>89</td>
</tr>
</tbody>
</table>
ACKNOWLEDGEMENTS

The document before you would not exist absent the support of countless friends, colleagues, teachers, and mentors whose lessons, conversations, ideas, and advice brought me to the conclusion of this project. My first and greatest debt of gratitude is to my advisor, Jinhua Zhao. His intellectual energy and passion for diving in to new research directions inspired me to find the right bridge between my interests in behavioral economics and the unanswered questions in planning research, and his tireless support, guidance, feedback, and encouragement were crucial to bringing my ideas to fruition.

Alongside Dr. Zhao, I’m also deeply grateful to my engineering and planning colleagues in the Travel Behavior and Transportation Policy lab, whose insightful and challenging comments helped me sharpen my thinking and anticipate challenges in the implementation of behavior change programming. Special thanks are due to Marisol Castro for her encouragement, critiques, and methodological advice. I’m also immensely grateful to Brittany Welsh, whose coding skills saved untold hours of manual data processing and opened up new experimental possibilities.

My friends and fellow planners at SCARP have been an extraordinary group of thinkers and doers to work and study alongside for the past two years—I’m constantly grateful for the passions and talents they’ve shared and the opportunity to imagine the future of planning alongside them.

I’m also deeply thankful to my instructors at School of Community and Regional Planning, as well as the teachers who helped me get here in the first place. At SCARP, two faculty members deserve special acknowledgment. Maged Senbel’s dedicated and passionate teaching on urban design was a highlight of my coursework in the program, and so I was delighted that he stepped up again to serve on my committee and provide helpful comments on my work. And in my first year of the program, Lawrence Frank’s teaching and supervision in the Health and Community Design lab was enormously helpful in developing both my abilities as a researcher and my passion for active transportation. I’m equally grateful to my
former teachers at the University of Wisconsin who went out of their way to help me chart a path towards
the planning profession: Alsi Gocmen, James Delehanty, and Jason Bittner.

Finally, I could not have completed this thesis without the unwavering support of the friends and family
who patiently listened to the ideas, challenges, thrills, and setbacks I grappled with throughout the
process; their intellectual and emotional support alike was essential and irreplaceable. I’m immensely
thankful for my academic family at Green College: your ideas and friendship alike are irreplaceable. I’ve
been privileged to have lived alongside each of the 150 or so Greenies of the past two years, but I’m
especially thankful to have met Nadia Stennes-Spidahl, Amanda Grochowich, Lorenzo Lane, Roland
Nadler, Rita McNamara, Richard Sandlin, Stacey Auld, Alex Cheng, Brittany Welsh, and Ben Blumer—
you’re all fantastic. Finally, I’m forever grateful to my parents, sister, grandfather, and aunts, uncles, and
cousins—my long academic journey is finally drawing to a close, and it’s meant the world to have you
standing behind me each step of the way. Thank you.
1. INTRODUCTION

1.1 Introduction: Applying Behavioral Findings to Transportation Planning

Understanding how people make decisions about when, where, and how to travel in their communities is a central challenge of transportation planning. Planners, engineers, and economists have developed a variety of modeling approaches to answer questions about travel decisions, and in particular how decision processes respond to economic factors: how will demand for transit service change as incomes rise? How will commuters adjust their journeys to a central business district if a congestion charge is implemented? Are consumer subsidies cost-effective at increasing the fuel efficiency of private automobiles? In these and many other questions, the models used to describe the decision-making process operate at different levels of detail and realism. Some seek to describe the steps a decision-maker follows in evaluating a new transportation option, while others abstract away from psychological processes to describe decisions in terms of economic calculations (e.g. mode choice models based on utility maximization) or even physical analogies (e.g. models describing traffic in terms of fluid flows). Regardless of the levels of explanation that different researchers employ when modeling these processes, however, human decisions are the foundational unit of behavior that planners and researchers seek to understand, predict, and influence.

Many of the objectives that planners, politicians, stakeholders, and society would like to achieve, such as reducing negative environmental externalities, improving public health, and reducing congestion and travel times, require exerting influence or persuasion on groups of travelers to change their decisions about mobility. The most straightforward means of changing the decisions of large numbers of people is by substantially altering the most visible characteristics of the choices in front of them, such as by adjusting the price or supply of a given travel option. As advertisers have long known, and policymakers are increasingly aware, changing the substance of a consumer choice is not the only way to affect
behavior. By altering the ways in which choices are presented to the decision-maker, planners and other transportation professionals can adopt the role characterized by Richard Thaler and Cass Sunstein as the *choice architect*, exerting influence over the direction of individual choices by determining aspects of the context in which decisions are made (R. Thaler & Sunstein, 2008).

In other areas of sustainability promotion, behavioral experiments have shown robust effects of interventions that alter the context of choice to reduce waste and energy consumption and encourage recycling. For example, a series of randomized field experiments conducted by the U.S. company OPOWER have extensively documented the potential for intermittent ‘Household Energy Reports’ to change peoples’ residential electricity use, producing a change in behavior equivalent to a 11-20% price increase (Allcott, 2011). The ability of purely informational interventions (or ‘nudges’) to significantly affect how people make small, everyday decisions in these domains suggests the possibility that transportation behavior, which likewise generates impacts through a large number of routine choices, may be influenced by interventions based on theories of how people respond to norms and cues in their environment.

Following from foundational explorations of how findings from behavioral economics and social psychology might be productively applied to problems in transportation planning (Gaker, Zheng, & Walker, 2010; Metcalfe & Dolan, 2012), this thesis examines the hypotheses that feedback on personal transportation behavior can play a role in reducing the negative impacts of motorized travel and encourage the adoption of sustainable and health-promoting modes such as walking and bicycling, and that mobile applications that passively monitor user travel behavior are an ideal platform for testing and implementing these behavioral interventions.
1.2 Challenges for Transportation Planners

Humans have relied on active transportation, defined as any mode of travel that relies on human power, as our primary means of mobility for practically all of our evolutionary history. Our bipedal gait and remarkable talent for endurance running distinguished early humans from other primates, and evolutionary biologists suggest that this talent may have given our ancestors a unique advantage at hunting and scavenging meat, enabling the evolution of “the unique human combination of large bodies, small guts, big brains, and small teeth” (Bramble & Lieberman, 2004). Only in the last century has ubiquitous access to motorized forms of travel in the industrialized world allowed city-dwellers to stop relying on modes such as walking, running, and bicycling. This shift has been simultaneously created and reinforced by massive changes in the built form of cities (Huang, Lu, & Sellers, 2007; Newman & Kenworthy, 2000), the travel and physical activity habits of urbanites and suburbanites (Brownson, Boehmer, & Luke, 2005), and the sustainability of urban systems (Newman & Kenworthy, 1999). Auto-centric patterns of development that have been established in the West are being rapidly replicated in developing countries across the globe, with similar benefits and costs (Bell, Ge, & Popkin, 2002).

The link between active transportation behavior and the physical infrastructure and spatial patterns of cities has been well established, and the health and sustainability benefits of replacing motorized trips with active ones are similarly well-supported (Frank, Schmid, Sallis, Chapman, & Saelens, 2005; Saelens, Sallis, & Frank, 2003). However, it is clear that while built form is an important enabler of walking, cycling, and other active modes, good infrastructure is not a silver bullet: inactive travel patterns are caused by a complex and interconnected set of factors ranging from utilitarian concerns (e.g. time, cost, reliability), to perceptions of comfort and social acceptability, to learned and habitual patterns of behavior that are rarely questioned or re-examined. Because of this variety of determinants of travel behavior, a multilevel or ecological approach that simultaneously addresses physical, societal, and individual barriers
to active travel is likely to produce better results than addressing any of these factors in isolation (Sallis et al., 2006).

1.3 Objectives and Methodology

1.3.1 Objectives

This thesis seeks to make several contributions to the literature on the relationship between behavioral science and transportation planning.

First, although researchers, planners, and policymakers have successfully developed a variety of responses to the physical, social, and economic impediments to active transportation, comparatively little work has been done to understand the decision-making processes by which individuals decide to adopt and maintain lifestyles that include active transportation. I suggest that a better understanding of this process may improve planners’ ability to predict what kinds of policies and messages can most effectively inspire changes in travel behavior. This thesis draws on the behavioral decision making literature with the goal of determining what sorts of contextual factors may influence individual decisions about whether to include active transportation in their everyday routines, as well as the relevance of this body of literature to other challenges in transportation planning.

Second, applications of behavioral decision research and social psychology to problems in other public policy areas have demonstrated the potential value of feedback-based interventions in the transportation domain. Drawing from the approaches to research and practice used in these areas, I seek to develop a methodological framework for designing, implementing, and testing different interventions under this umbrella. I examine how mobile technologies and randomized controlled trials can provide a robust basis for testing the effects of different behavioral nudge designs, and discuss how transportation practitioners,
non-profit organizations, and researchers can engage in mutually beneficially collaborations to test this approach.

Third, I investigate the feasibility of conducting behavioral intervention experiments based on a commercially available activity tracking application for smartphones. Through two pilot studies conducted with students at the University of British Columbia and participants in ‘Bike to Work Week’ programs in British Columbia and Minnesota, I examine the effectiveness of recruitment strategies, user satisfaction with the activity tracking application and feedback reports, and evidence of behavior change.

Finally, I seek to expand on what a broader research program for applying the techniques of behavioral nudging to promoting healthy and sustainable travel choices might involve. I provide a sketch of how larger-scale experiments of this kind might be conducted, and how researchers and their partners in the planning and advocacy communities might apply this approach to interventions that provide concrete benefits for users, advance the policy objectives of institutional stakeholders, create useful data sources for research, and allow for the development of best practices for active travel promotion.

1.3.2 Methodology

I develop the thesis’ overall framework for behavioral interventions based on the literatures on consumer behavior in behavioral economics; experimental approaches in economics and public policy; and active travel promotion and travel data gathering. To test the effectiveness of the behavioral intervention and data-gathering framework described in this thesis, I conduct two field experiments using a randomized controlled trial design, providing each participant with a mobile application to measure their active travel and using the data gathered from the app to generate a personalized feedback form that includes either basic (control) or enhanced information about the impacts of their travel patterns.
1.4 Outline

The remainder of this thesis is structured as follows:

Chapter 2 introduces the history and major findings of the behavioral economics literature, aimed at providing planning researchers and professionals unfamiliar with this field a sense of how behavioral economists combine the characteristic methodologies of both psychology and economics into an interdisciplinary body of knowledge with enhanced predictive and explanatory power, especially in the domain of small-scale phenomena such as transportation decisions. Existing and potential applications of this literature to other problems in planning practice are also discussed.

Chapter 3 lays out the theoretical foundations for applying mobile technology to behavioral interventions on transportation behavior. The three pillars of this approach—behaviorally-inspired design, app-based measurement, and assessment based on randomized controlled trials—are explained and justified. Using this foundation, I describe the many parameters that a researcher must consider when developing a behavioral intervention strategy, and recommend particular combinations as promising designs for future implementations.

Chapter 4 presents the results of two pilots of a basic behavioral intervention. The first, conducted at the University of British Columbia, provides an initial test of the Moves platform for collecting travel behavior data and user responses to feedback reports. Using lessons from this initial test, I conducted a larger-scale pilot of Bike to Work Week (BTWW) participants in British Columbia and Minnesota in partnership with three active travel advocacy organizations. Data collected from this pilot shows promising results, with some indications of behavioral change and very favorable user responses to the app and feedback system. The experiment also builds a foundation for continuing partnerships between the research team and BTWW program managers.
Chapter 5, written in collaboration with Brittany Welsh, explains the design and implementation of a web app for automating data-gathering functions through the *Moves* API. This software reduces the effort necessary to collect travel data for both the researcher and participant, simplifies the process of sending feedback, and enables the collection of more detailed trip and location data from participants.

Chapter 6 describes two additional experimental designs intended to provide stronger evidence of the effectiveness of behavioral interventions. By using the more fully automated data gathering system described in Chapter 5, more detailed data can be collected at a lower level of user burden, allowing scaled-up recruitment and reduced attrition of the course of these studies. A study conducted amongst Amazon Mechanical Turk users will allow for a larger, more reliable sample size as well as a sharper contrast between control and experimental feedback designs. A second study conducted amongst BTWW participants in Minnesota will leverage social media and strong prior user reviews to test a snowball sampling approach.

Chapter 7 provides a conclusion to the thesis, summarizing the important findings of this research, as well as the limitations of the framework and results presented. I discuss the implications of this line of research for transportation practice, as well as presenting directions for future investigations of travel behavior using behavioral economics, experimental methods, and mobile technology.
2. A BRIEF INTRODUCTION TO BEHAVIORAL ECONOMICS

2.1 Introduction: The History, Findings, and Applications of Behavioral Economics

Behavioral economics is an interdisciplinary field that brings together theoretical and methodological approaches from both psychology and economics to produce better theories, more accurate predictions, and more nuanced understandings of economic phenomena. Because many of the processes that urban planners seek to understand, predict, and change involve distinctly economic sorts of activities, behavioral economics stands to contribute greatly to the study and practice of planning, especially in relation to questions of location choice and travel decisions. In this chapter, I provide a brief explanation of how behavioral economics emerged and where it stands in relation to economics and psychology, as well as a summary of the field’s most important findings. I then turn to a discussion of how behavioral economics might inform planning practice and research, with a particular focus on issues and challenges in transportation.

2.2. A Short History of Psychology and Economics

In the modern academy, many practitioners of both psychology and economics might make strong claims for their disciplines as the most ‘scientific’ of the social sciences. Both employ sophisticated quantitative methodologies and deep bodies of theory, and each have made vast contributions to how laypeople and experts across a host of other fields conceptualize the social world. Yet for several decades through the 20th century, the two fields pursued highly separate and independent research programs, with very little interaction between researchers in each discipline. Explaining how these disciplines lost the ability to interact, and how behavioral economists were able to bring them back into contact with each other, hinges on an understanding of the methodological and epistemological positions taken by each field over time.
In the 19th century, both economics and psychology were in their infancy, and practitioners of both fields were struggling to emerge from their philosophical roots and borrow from the great successes of natural sciences such as physics and biology. However, the distinctions between these two nascent sciences were blurry:

“Many economists moonlighted as the psychologists of their times. Adam Smith, who is best known for the concept of the "invisible hand" and *The Wealth of Nations*, wrote a less well-known book *The Theory of Moral Sentiments*, which laid out psychological principles of individual behavior that are arguably as profound as his economic observations” (Camerer & Loewenstein, 2004)

In economics as well as psychology, theorists and researchers were broadly comfortable in speaking about peoples’ mental states and cognitive and emotional processes. While economists are today often associated with psychologically simplistic notions of well-being and self-interest, classical economists were engaged in debates about the nature and causes of human well-being, and were perceptive observers of the nuances of these questions: Adam Smith, as well as many of his contemporaries and early neoclassical followers, were engaged with sophisticated issues such as temporal inconsistencies in preferences, and commitment devices people use to regulate their future behavior (Palacios-Huerta, 1992).

However, psychological theorizing in the field began to evolve in the direction of greater analytical tractability with the early neoclassical economists. Inspired by Benthamite conceptions of pain and pleasure as unitary ‘sovereign masters’ provided a rubric under which utility could be conceptualized in terms of aggregated happiness over different individuals’ mental states, economists such as Jevons and Pigou were able to rationalize assumptions that have become critical features of economic analysis—“the completeness and transitivity of the preference relation [and] the convexity of indifference curves”—
while also allowing for irrational behavior resulting from mistakes in anticipating future pains and pleasures (Angner & Loewenstein, 2007).

However, a set of countervailing forces arose in the years before and after World War II that pushed economics in a different direction. Dissatisfaction with the slow progress of the discipline’s predictive power under the hedonic framework created a demand for new approaches, and the rise of behaviorism in psychology created a methodological alternative based on the premise that “scientific methods should be public (thereby reject[ing] the use, e.g., of introspection)... and focus on behavior only (thereby avoiding references to unobservables such as beliefs, desires, plans, and intentions)” (Angner & Loewenstein, 2007). To this view, cognition—the mental processes that take place between stimulus and response—is irrelevant to scientifically explaining behavior, as are unobservable mental entities like ideas, plans, desires, and representations. Drawing also on operationalism in physics, economists sought a minimalistic conception of economic behavior that minimized its dependence on any particular psychological foundation.

The concept that met this criterion and became central to postwar neoclassical economics was preference, defined not in terms of particular mental constructs but as a more primitive ordering relation between different options, goods, or (most generally) states of the world. Preference relations are agnostic about economic agents’ underlying motives; the object of economic investigation is not how people come by their preferences but how they act in light of them. While neoclassical economists did not jettison the notion of utility altogether, its meaning changes in light of this methodological shift. Utility is no longer identical to well-being, pleasure, or any other substantive good; the statement “A has greater utility than B” is synonymous to “A is preferred to B,” which—in keeping with the behaviorist emphasis on observability—is operationally interpreted simply to mean that the agent has chosen A instead of B.
This framework, called *ordinalism*, provided economists with a theory that could be pursued independently of psychology and investigated deductively and mathematically based on axioms enabled by this definition of preference. Neoclassical economics thereby gained much in terms of building a generalizable, mathematical, and (at least potentially) predictive body of models and theories, but the trade-offs were steep: it lost all meaningful accounts of “deliberation [or] how preferences are formed,” its “theoretical basis for the assumptions on preferences,” and “its theoretical resources to describe irrational behavior” (Angner & Loewenstein, 2007). Compounding its losses, this turn in economic theory also cut the field off from meaningful dialogue with psychologists.

This schism is in large part a function of the different methodologies adopted by the two disciplines in the 20th century. The highly deductive apparatus of economics, especially in the postwar era, sharply contrasts with the more inductive approach of experimental psychology. Broadly speaking, economists build theory by deriving implications about agents, institutions, and markets from axioms and assumptions: non-obvious products of these deductive exercises are the object of the work, and accuracy or correspondence to real-world phenomena are often treated as a secondary consideration to the analytical result itself. By contrast, the principal method of psychology is that of hypothesis testing through lab and field experiments; while deductive approaches are important to theory-building, theories are judged by their fit with experimental results in comparison to competing theories (Hilton, 2008).

The greater theoretical diversity enabled by this more inductive approach in psychology allowed for the emergence of an important break from behaviorism in the 1950s and 1960s. The ‘cognitive revolution’ of this era, influenced by emerging fields such as computer science and neuroscience, arose as psychologists realized that theorizing about mental processes and information processing was necessary to explain certain kinds of behavior (Miller, 2003). Simply examining the relationship between environment and behavior, they realized, is inadequate without the mediating factors that take place in the mind. While cognitive psychologists sympathized with the behaviorists on the necessity of publically available
evidence for scientific progress to occur, focusing on behavior as both the only acceptable evidence and the only acceptable theoretical entity made robust investigations of “questions about the nature of human language, planning, problem solving, imagination, and the like” nearly impossible (Gardner, 1987).

Cognitive psychology, by contrast, took mental constructs and the specific mechanisms by which the brain processes, organizes, and acts on information to be important determinants of behavior, and sought ways to investigate these phenomena in an equally rigorous way. The analytical apparatus to revisit questions of mind in psychology came from a broad interdisciplinary background: mathematical logic informed both Turing’s conception of computation and McCulloch and Pitts’ understanding of neural activity; the synthesis of feedback, control, and communication in the field of cybernetics; and Shannon’s theory of information (Gardner, 1987).

The cognitive revolution turned out to be vital not only to numerous successful research programs in psychology, but also to the development of focused and accessible critiques of the assumptions of neoclassical models and theories. By bringing cognition into the realm of psychological inquiry, the discipline regained the theoretical tools necessary to explore questions of how people make decisions. Behavioral decision research arose as a distinct branch of psychology concerned with the application of computational models to human choices (Angner & Loewenstein, 2007). Within economics, a complementary development was in progress: the development and refinement of expected utility models created more specific and testable predictions of how agents behave, as well as a standard for optimal behavior in economic decision processes. Expected utility theory, for example, predicts that agents discount future outcomes in a consistent and predictable way; that less-preferred alternatives have no influence on the utility of a chosen alternative; and that possible losses and gains are evaluated in the same way. All of these provided “hard targets” for psychologists interested in economic behavior (Camerer & Loewenstein, 2004).
The confluence of testable predictions of how economic agents behave and a psychological framework for dealing with cognitive decision processes created a new opening for interdisciplinary researchers to provide compelling critiques of neoclassical assumptions. Prior to this point, economists interested in psychology and irrationality, such as Simon and Scitovsky, had achieved little progress in broadening the foundations of economic theory. By the 1970s, however, a group of psychologists who were conversant in the mathematical language of academic economists began to test how rational, utility-maximizing decision making plays out in the real world. The most well-known example of this approach appeared in the contributions of Tversky and Kahneman, two psychologists who published a series of papers in the 1970s demonstrating systematic deviations from expected utility theory when people face decisions involving uncertainty and developing an alternative framework for understanding these decision processes, called prospect theory. Kahneman and Tversky’s contributions set a model for future work in behavioral economics:

“First, identify normative assumptions or models that are ubiquitously used by economists, such as Bayesian updating, expected utility and discounted utility. Second, identify anomalies—i.e., demonstrate clear violations of the assumption or model, and painstakingly rule out alternative explanations (such as subjects’ confusion or transactions costs). And third, use the anomalies as inspiration to create alternative theories that generalize existing models. A fourth step is to construct economic models of behavior using the behavioral assumptions from the third step, derive fresh implications, and test them” (Camerer & Loewenstein, 2004).

The third step discussed here—the creation of alternative models—is central to what makes behavioral economics a branch of economics, rather than merely a psychological critique of it. By adopting both the inductive methods of experimental psychology and the deductive, mathematical framework of economics, new frameworks such as prospect theory demonstrate that more psychologically realistic agents can still be modeled in a tractable way. As Camerer and Loewenstein put it, “At the core of behavioral economics
is the conviction that increasing the realism of the psychological underpinnings of economic analysis will improve economics on its own terms—generating theoretical insights, making better predictions of field phenomena, and suggesting better policy.” By taking the improvement of economic research seriously, Kahneman and Tversky’s 1979 paper “Prospect theory: An analysis of decision under risk” had enormous influence within the discipline and brought the behavioral approach to the attention of mainstream economists (Camerer & Loewenstein, 2004).

2.3. Core Findings of Behavioral Economics

2.3.1 The Methodology of Behavioral Economics

Behavioral economics today has become increasingly successful at bridging the gap between the highly deductive, axiomatic, and analytical approach of conventional economics and the more inductive and experimental methods of psychology, in particular “the method of strong inference that is characteristic of mature experimental sciences” (Hilton, 2008). It brings a greater emphasis on realism and a willingness to examine the principles on which models are built, and in particular to see if modeling assumptions that show signs of being systematically misleading or empirically false can be replaced with constructs that better represent real-world phenomena without excessively increasing the complexity of the model. While not synonymous with experimental economics, many behavioral economists display a strongly experimental or empirical streak. For example, many foundational findings in behavioral game theory emerged as a result of laboratory tests of game theoretic predictions of behavior in settings such as public goods games, prisoner’s dilemmas, and ultimatum games (Thaler, 1994).

The result of this methodological orientation is a body of findings concerned broadly with the ways in which the decision processes of economic actors diverge from the canonical homo economus model in neoclassical microeconomic theory, as well as attempts to represent these findings through mathematical models. These findings include the effects of inconsistent preferences or preferences for fairness and others’ welfare; decision-making using heuristic processes, rules of thumb, or biased reasoning, and how
context affects structurally similar decisions; and inconsistent responses to decisions and consequences across time or under uncertainty. In addition to examining and modeling non-standard decision-making processes and the conditions under which they occur, some behavioral economists also investigate the measurement of economic outcomes with non-economic indicators, such as measures of satisfaction or subjective well-being.

An example of the behavioral economic research program in action is presented by an experiment conducted with a group of daycare providers in Israel (Gneezy & Rustichini, 2000), in which parents picking up their children after the closing time of the facility had become problematic. Because both psychological theories of punishment and standard economic theory predict that a financial penalty would serve as a deterrent to this sort of behavior, the experimenters collaborated with a randomly selected group of daycares to institute a fine (equivalent to about $3 USD) on parents who arrived late, while a control group maintained the existing policy in which no penalty was specified. This seems to be a straightforward application of the principle that discouraging a behavior can be easily accomplished by putting a price on it. However, the authors found that rather than reducing the number of latecomers, the fine increased the rate of late arrivals. By way of explanation, they propose that the introduction of a monetary fine had the effect of shifting the perception of the kind of transaction taking place when a parent collects their children past the specified time. As the authors put it:

“Parents may have interpreted the action of the teachers in the first period as a generous, nonmarket activity. They may have thought: ‘The contract with the day-care center only covers the period until four in the afternoon. After that time, the teacher is just a nice and generous person. I should not take advantage of her patience.’ The introduction of the fine changes the perception into the following: ‘The teacher is taking care of the child in much the same way as she did earlier in the day. In fact this activity has a price (which is called a ‘fine’). Therefore, I can buy this service as much as needed.’”
As the authors sum up in the title of the article, “A Fine is a Price,” attaching a price to a formerly non-market good can result in replacing a strong disincentive provided by a social norm with a weaker disincentive provided by a monetary cost. Moreover, they found that even after discontinuing the fee system, increased levels of late arrivals persisted, indicating that the norm could not easily be reinstated after parents had become used to thinking of care after closing time as a market activity. While they note that a sufficiently large fee would probably serve to reduce late arrivals, the nominal fee instituted in their experiment resulted in the opposite of the intended effect.

Gneezy and Rustichini’s experiment is an illustrative example of several important characteristics of policy-oriented research in behavioral economics. First, it examines a phenomenon that has an important economic component; here, the costs imposed by parents on daycare providers in the form of uncompensated work time. Second, it takes a prescription that seems like a plausible solution from the perspective of standard economic reasoning (in this case, economic analysis of punishment and crime deterrence) and compares it to psychological research, with an eye towards understanding differences in methods, reasoning, and findings across disciplines. Third, it applies an empirical test of the proposed effect, in this case through a randomized controlled trial, in order to provide a strong test of the hypothesized relationship. Lastly, it provides an explanation for its results in a way that sheds new light on the conditions under which standard economic theory will predict behavior well, and when those conditions fail to hold because of motivations or decision processes outside the scope of conventional models. In the policy context, it provides guidance for anticipating unintended consequences and preventing regulations from backfiring.

In the following sections, I will present a representative sampling of important findings and effects from the behavioral economics literature. The findings of behavioral economics are difficult to sum up under a single principle; in comparison to the theoretically tidy axioms of rational choice theory, the wide array of
effects, heuristics, biases, and other anomalies lumped together under the heading of ‘behavioral economics’ can seem disorganized and fragmented. However, many of the important insights that the field has produced can be described briefly with a few principles: people make choices (especially choices involving uncertainty) and manage resources using shortcuts and rules of thumb that allow irrelevant or manipulated contextual factors to influence decisions; people value fairness, equity, and other people as well as their own well-being; and although many of these effects are adaptive in most circumstances, they can cause both poor individual decision-making as well as broader market failures.

2.3.2 Heuristics and Biases

The most well-known set of effects in behavioral economics are those described in the heuristics and biases research program. Pioneered by Kahneman and Tversky, this body of research is built on the foundational premise that our mental equipment for decision-making includes a number of shortcuts, or heuristics. Heuristic reasoning allows us to avoid spending time and mental effort on difficult calculations and is, in everyday situations, generally able to produce comparable results to the more detailed sort of utility calculations that inform the normative standard of rational decision-making. However, heuristics are also prone to systematic errors, or biases, that result in predictably mistaken judgments. The predictability of these errors is central to the research program: because biases operate in predictable contexts and produce a predictable directionality and magnitude of the error, knowledge of heuristics and biases can provide avenues to improve judgements, predictions, and decisions by correcting or compensating for the bias.

Kahneman and Tversky described three of the most important heuristics in their seminal article, “Judgment Under Uncertainty: Heuristics and Biases”: representativeness, availability, and anchoring and adjustment (Tversky & Kahneman, 1974). These, along with the more recent formulation of the affect heuristic (Finucane, Alhakami, Slovic, & Johnson, 2000) provide the foundation of many observations of
systematic irrationality in economic decisions. Each of these heuristics is a way of simplifying complex calculations of quantities and probabilities by generalizing from more easily accessible information.

The *representativeness* heuristic states, generally, that people often evaluate “the probability that process $A$ will generate event $B$” by determining “the degree to which $A$ is representative of $B$, i.e., by the degree of similarity between them.” One of the canonical examples of how people use this heuristic and therefore make reasoning errors is the “Linda Question,” in which subjects are asked to judge the probability of a set of statements about Linda, described as follows:

“Linda is 31 years old, single, outspoken, and very bright. She majored in philosophy. As a student, she was deeply concerned with issues of discrimination and social justice, and also participated in anti-nuclear demonstrations” (Tversky & Kahneman, 1983)

Respondents were asked to estimate the probability of a set of descriptions of Linda being true, including the statements “Linda is a bank teller” and “Linda is a bank teller and is active in the feminist movement.” Elementary probability theory teaches that $P(A\&B) \leq P(B)$—the conjunction rule—and therefore any subject reasoning correctly about this proposition should note that the second statement is less likely than the first. However, because the description of Linda as a feminist bank teller more closely matches how she is described, a subject operating on the representativeness heuristic might judge the second statement (the conjunction) to be more likely. In an early experiment, Tversky and Kahneman found that this effect was quite prevalent, with 85% of undergraduate respondents judging that Linda was more likely to be a feminist bank teller than a bank teller. Numerous replications in different populations have shown that the effect is robust across many conditions, including among statistically sophisticated populations and in experiments in which the problem is framed differently, e.g. as bets rather than probability estimates (Sides, Osherson, Bonini, & Viale, 2002)
The representativeness heuristic can operate through other mechanisms as well. Subjects have been found to inadequately consider sample size when assessing the strength of evidence and overestimate the representativeness of small populations, and judge repetitive sequences of IID events as less likely than ‘random-looking’ ones (e.g. a series of six coin tosses producing HHHTTT is judged less likely than one producing HTHTTH). The consequences of this last phenomenon can be seen in the gambler’s fallacy, in which people erroneously believe that a string of the same outcome (e.g. five coin tosses coming up heads in a row) implies that the odds of a different outcome are elevated for the next test (e.g. tails is more likely to come up in the next toss).

The availability heuristic is seen when the probability of some event is determined by how easily examples of it can be called to mind. Information that is easy to recall or search for is likely to be overweighted, and scenarios that are easier to imagine are judged as more likely than those that are more difficult to visualize. A clear example from the transportation and risk communication literature is in peoples’ assessments of the riskiness of different modes of travel. While modern risk estimates show that air travel is safer on a per-passenger-mile-traveled basis than driving under the vast majority of possible circumstances (Sivak, Weintraub, & Flannagan, 1991), the impression of air travel as more dangerous persists. This misconception can be explained by representativeness: although automotive travel claims hundreds of times more lives than air travel, high-profile plane crashes and terrorist incidents receive far more attention and media coverage, and therefore can be brought to mind more easily. An extreme instance of this phenomenon was seen in the reaction to the attacks of September 11, 2001, in which significant decreases in air travel resulted in an estimated 350 lives lost due to substitutions from air travel to automotive journeys during the last months of that year—a significantly greater toll than the 266 passengers killed on the four flights that were hijacked (Gigerenzer, 2004).

The adjustment and anchoring heuristic refers to a two-part estimation strategy that people may use to estimate quantities, including their own willingness to pay for goods. An initial value that may or may not
be associated with the quantity to be estimated is taken as a starting point, and then adjusted upwards or downwards to take into account other information known about the quantity in question. However, adjustments tend to be insufficient to eliminate the effect of the starting value, allowing an irrelevant anchoring value to exert influence on their estimate or price. Early experiments showed this effect when asking subjects to make bets on uncertain future events and estimate unknown quantities. For example, a group of subjects were given a randomly chosen starting value between 0 and 100 and asked to estimate quantities like the percentage of African countries in the United Nations; those who had received higher anchors responded with significantly higher median estimates (Tversky & Kahneman, 1974).

More significantly, this effect has also been shown in studies of subjects’ willingness to pay and willingness to accept for familiar consumer goods. In a study of MBA students, subjects were prompted to write down the last two digits of their social security number (as an anchor); indicate whether they would be willing to pay that number in dollars for good such as chocolates, bottles of wine, and computer accessories; and write down maximum bids for the items. Analysis of these bids found a strong effect: students with the highest social security numbers bid two to three times as much as those with the lowest numbers for the same goods! However, differences in quality between goods are still incorporated into bids, suggesting that while anchoring biases the bids across a range of products significantly, adjustment allows those bids to express preference coherently, relative to the anchor (Ariely, Loewenstein, & Prelec, 2003).

Finally, the affect heuristic has been developed as an additional decision-making mechanism, in which people use their affective responses to choices in place of calculations of cost and benefit. While the heuristics identified by Kahneman and Tversky above reflect strategies for lessening the burden or complexity of essentially cognitive decision-making processes, the affect heuristic describes a decision-making process in which the goodness or badness of the subjective impressions that people associate with an option becomes a cue for evaluating both the risk and the benefits of that choice (Finucane et al., 2003).
This departs from earlier research that, occasional acknowledgements of emotional decision-making notwithstanding, primarily investigated the cognitive processes by which people form and act upon reasons that guide choice (Shafir, Simonson, & Tversky, 1993).

An early investigation of risky choices by Finucane et al. hypothesized that affective impressions of objects and events are easy to access and can supplant evaluations of both the benefit and riskiness of a choice, leading to an artificial negative correlation between perceptions of risk and benefit. Under conditions of time pressure, in which heuristic strategies become important for rendering a judgment in the time available, the authors found that negative correlations between perceived risk and perceived benefit were significantly more common than among respondents under no time pressure in assessments of 11 out of 23 risk assessment items (such as alcoholic beverages, food preservatives, and chemical plants). In a follow-up study, the authors also found that manipulating the perceived riskiness of an item produced a significant and negatively correlated change in its perceived benefit, and manipulating its perceived benefit produced a similar effect on its perceived riskiness (Finucane et al., 2000).

These findings suggest that, across a broad domain of public policy and private consumption choices, evaluations are influenced by affect-laden messages, and that positive affective associations in one evaluation domain (e.g. risk) are generalized to other domains (e.g. potential benefits) for that object. Evaluations are also heavily influenced by the degree to which affective meanings can be attached to a piece of information. In a particularly vivid example, individuals asked to rate a safety policy expected to save 150 lives at risk expressed weaker support than individuals presented with an otherwise identical policy expected to save 98%, 95%, 90%, or even 85% of the 150 lives. As the author describes:

“Saving 150 lives is diffusely good, hence only weakly evaluable, whereas saving 98% of something is clearly very good because it is so close to the upper bound on the percentage scale,
and hence is readily evaluable and highly weighted in the support judgment” (Slovic, Finucane, Peters, & MacGregor, 2007).

These and other heuristics allow for many predictions about the conditions under which biased reasoning will occur in economic decision-making. Uncertainty about risk, especially risks that are difficult to quantify, creates many opportunities for irrelevant information to affect evaluations and decisions. However, as we shall discuss later in this chapter, not all heuristics are harmful in all circumstances: many are generally adaptive and only cause problems in a narrow set of circumstances. Nevertheless, the heuristics and biases program provides valuable insights into how people may respond to decision contexts shaped by marketing, policy, and institutional arrangements.

2.3.3 Fairness, Cooperation, and Altruism

As a subfield of economics, game theory has done much to uncover the logic of strategic behavior, including the conditions under which cooperative behavior can occur. Because game-theoretic analysis generally assumes (as in other microeconomic theory) that participants can be accurately modeled as rational and self-interested, its notions of normatively optimal strategies provide a clear standard of whether or not *homo economicus* assumptions are being met in real play. Therefore, an important line of research in behavioral economics has involved testing the predictions of game theory against peoples’ actual behavior: if consistent deviations from game-theoretic predictions are observed, we can infer that participants are either making errors in how they play, pursuing goals other than maximizing their own earnings, or playing by the logic of social norms rather than economic calculation. In general, these experiments have taken place in the lab and involve participants acting as players in various economic games, such as prisoner’s dilemmas, public goods games, and ultimatum games, while experimenters manipulate variables irrelevant to the logic of the game, such as social context.
The public goods game provides an excellent platform for understanding cooperative behavior. The game abstracts the problem of providing public goods in general, which are defined by “two properties: (1) once it is provided to one person, it is costless to provide to everyone else; (2) it is difficult to prevent someone who doesn’t pay for the good from using it” (R. Thaler & Dawes, 1992). Under standard economic assumptions, agents who have a choice of whether or not to contribute to the provision of a public good will avoid doing so and “free ride” on the contributions of others (e.g. listening to public radio but not donating towards its operation). In order to simulate this sort of situation, participants in public goods experiments are placed in groups, given a starting allocation of money, and informed that whatever money they finish the experiment with will be theirs. In one or more rounds, each member of the group must choose between keeping their money or investing some or all of it in a ‘public good’. All money invested in the public good that round is multiplied by some factor (greater than 1 but less than the size of the group) and redistributed evenly to all participants.

Under these conditions, the group as a whole benefits from a greater level of contribution, but each participant faces a negative expected value if they contribute. For example, consider a group of four players in which contributions to the public good are doubled. A player who invests $10 in the public good will generate $20 for the group (doubling their money) but will only personally receive $5 of their investment back. If the other three players contribute in a round, a contributing player will receive a total of $20 back ($40 multiplied by two and divided by four players is $20 per player), whereas a free riding player will end the round with $25 ($30 multiplied by two and divided by four players is $15 per player; add the free rider’s original $10 and she leaves with $25). Therefore, economic theory predicts that no one will contribute to the public good.

Tests of the outcome of public goods games in both one-shot and repeated formats have shown that, contrary to this prediction, substantial numbers of participants do contribute to the public good across a range of conditions. While early trials of one-shot public goods games found participation rates of 40 to
60 percent in most groups, questions were reasonably raised as to whether this effect would persist over
time, and initial trials indicated that rates of cooperation decline substantially with subsequent rounds (R.
Thaler & Dawes, 1992). A clear hypothesis as to why this might be the case is that participants simply do
not understand the game or the correct strategy to use at first, and learn over time that playing less
cooperatively leads to better results. However, clear evidence exists that this is not the case: simply
restarting the game with the same group of participants causes rates of cooperation to jump back to their
original level (Andreoni, 1988).

This result suggests two alternate possibilities: either the participants are altruistic (that is, they desire to
make others better off—or at least wish to appear as if they do) or they may be practicing reciprocal
altruism (that is, participants calculate that appearing cooperative enhances the chances of other players
reciprocating and active cooperatively themselves, to one’s ultimate benefit). The latter is a rational
strategy in some repeated games, although in games with a known endpoint the strategy breaks down.¹
However, experimental trials of such games rule out this explanation, as cooperation is maintained even
in the last period of finite repeated games (when it can never be advantageous to cooperate) and in finite
repeated games in which the group each participant plays with changes on each round. Thaler describes
this phenomenon as a “norm of cooperation,” which dictates that people generally cooperate with each
other until they’re taken advantage of; this norm is strengthened considerably in experiments where
participants are allowed to talk to each other. Perhaps the best illustration of this norm is that groups in
which participants made promises to each other to cooperate saw substantially higher rates of cooperation
if every participant made the same promise. If one or more participants refused to promise, other
participants became no more likely to cooperate than if they had not made the promise in the first place,
suggesting that the commitment to cooperate is in fact conditional on everyone else’s conditional

¹ “In any finite game both players know that they should defect on the last trial, so there is no point in cooperating
on the penultimate trial, and by backward induction, it is never in one’s best interest to cooperate” (R. Thaler &
Dawes, 1992).
commitment. These results indicate that, contra traditional game theoretic predictions, rational self-interest is a poor (or at least incomplete) description of actual human behavior in dilemmas of this sort, and that a variety of motivations, including both pure and reciprocal altruism and self-interest, govern behavior.

A similar line of investigation has examined how people approach an even simpler scenario: the ultimatum game. In this game, one player is designated as the allocator and the other as the recipient. The allocator is asked to propose a division of a pool of money between him or herself and the recipient, and the recipient may either accept this division or reject it, in which case neither player receives any money. Conventional game theory suggests that the allocator propose the division most favorable to him or herself that still leaves the recipient with a real gain—however small—from the division (e.g. allocator receives $9, recipient receives $1). Experimental tests of this game find, however, that recipients often decline positive offers that are perceived as too low, and allocators often make offers that are considerably more generous to the recipient than predicted, suggesting that considerations of fairness enter into both players’ decisions (R. Thaler, 1992).

2.3.4 Mental Accounting of Consumption, Spending, Investments, and Losses

When economists model the decisions of households and firms in deciding how to allocate their resources, standard theory lumps all of the decision-maker’s assets—cash and bank accounts, discounted future income flows, and equities and real estate—into one overall pool, measured by the present value of the entity’s wealth. If the assumption of fungibility is accurate, the form that wealth takes is irrelevant to consumption decisions.

However, numerous examples demonstrate that people often pursue a different strategy. Rather than treating all wealth as a common pool to allocate from, people often create budgets and make spending and investment decisions by designating funds for specified purposes. Different expenditures are lumped
together and evaluated individually in order to lessen both the cognitive and emotional demands of evaluating numerous potential gains and losses in day-to-day decision making. Three distinct models describe levels at which mental accounting can take place. In the simplest case, a minimal account frames the problem as a comparison between two options, isolating all but their divergent features. A topical account poses a choice between several options in comparison to a context-dependent reference level. Finally, the comprehensive account posits a calculation between all other factors affecting the decision-maker, including overall wealth, assets, and earnings; this frame is equivalent to the assumptions of standard economic models (R. Thaler, 1999). Mental accounting research is primarily concerned with the second class of accounting schemes, and in particular the difference in peoples’ perceptions and behavior when similar income, expenses, and consumption are placed in different topical accounts.

Many predictions about how mental accounting influences choice are derived from prospect theory, which incorporates several important features of human decision-making into a similar mathematical form as conventional expected utility theory. Where expected utility theory models decisions in terms of their effects on absolute consumption or wealth, prospect theory models decisions as evaluations of gains and losses relative to a reference point. Where expect utility models general assume a utility function that is convex throughout (displaying diminishing marginal utility at every level of wealth), prospect theory follows from psychophysics and proposes a concave gain function and a convex loss function; that is, people’s marginal sensitivity to both gain and loss diminishes as quantities increase in either direction. Finally, while expected utility theory evaluates only the final level of wealth or consumption obtained, prospect theory incorporates the notion that losses are painful to a greater degree than gains are pleasurable (Kahneman & Tversky, 1979).

Based on this set of assumptions, several important predictions can be made. First, Thaler notes that the concave gain function and convex loss function of prospect theory agents—informally, the fact that people exhibit declining sensitivity to both gain and loss as a prospect becomes farther from the reference
point—leads to several predictions about when people will choose to integrate or segregate gains and losses:

- When experiencing several gains, account for each gain separately to maximize pleasure
- When experiencing several losses, account for all losses as one combined loss to minimize pain
- When experiencing a small loss and a large gain, account for them together to eliminate the pain of experiencing any loss
- When experiencing a small gain and a large loss, account for them separately to preserve the pleasure of a “silver lining”

In experiments that ask participants to assess the well-being of hypothetical subjects that receive these combinations of gains and losses in integrated or separated accounts, peoples’ perceptions of how best to account for gains and losses appear to match these predictions (R. Thaler, 1999).

Another prediction is that people may make suboptimal decisions when faced with the prospect of ‘closing’ a particular account at a loss. While rational analysis may favor liquidating an asset that has declined in value (e.g. on the basis of its poor expected future performance, or for tax purposes), doing so involves realizing a painful loss. While analyzing the choice from the perspective of the comprehensive account may reveal that realizing a loss in one investment may be the best course of action for the investor’s portfolio as a whole, evaluating the decision in a topical account frame highlights the fact that the investment has taken a loss relative to the reference point of its initial value. Empirical analyses of investor behavior have found evidence that investors behave in this manner, attempting to avoid taking specific losses even at the expense of their overall returns (Odean, 1998).
Similar inconsistencies can also be observed in situations where people have made purchases in advance of consuming them. The purchase creates an account that is expected to be balanced by later consumption or enjoyment of the purchase; if the opportunity to do so is lost, the account is suddenly brought to conscious attention as a loss. An example is a basketball fan who, having purchased an expensive ticket in advance, suddenly finds themselves caught in a snowstorm that will make reaching the game difficult and hazardous. Compared to a similar fan who had merely planned to attend the game but had purchased no ticket in advance, the fan with the pre-purchased ticket perceives the sunk cost of the ticket as a suddenly salient loss, and is predicted to be considerably more motivated to drive through the snowstorm to attend the game to avert this loss (R. Thaler, 1980).

Ambiguities are especially likely to occur when consumption and purchase are separated by considerable lengths of time. A survey of wine collectors found that purchasing wine that will not be consumed for several years is commonly viewed as an investment (not consumption spending), while consuming it in the future is commonly perceived as being free (having been paid for years in the past) or even as saving them money (because the initial expense was less than its market price at the time of consumption), making the enjoyment of a valuable good much less aversive than if it had to be paid for at the time of consumption. By accounting for expenditures in this fashion, the purchaser never experiences a loss associated with consuming the wine—as Thaler describes, “this mental accounting transforms a very expensive hobby into one that is ‘free’” (R. Thaler, 1999). More generally, this finding suggests that the aversiveness of different kinds of consumption is closely tied to how it is framed and accounted for, and that consumption of goods purchased in the past or use of durable goods is often accounted for as free (Shafir & Thaler, 2006).

2.3.5 Bounded and Ecological Rationality

Behavioral economists have spent a great deal of time and energy predicting, testing, and documenting the circumstances in which heuristics, preferences for fairness, and mental accounting habits produce
behavior that, by the normative standards of microeconomics and game theory, is irrational and sub-optimal. Many of the biases and effects in this literature produce unambiguously poor outcomes: people invest less than they should, fail to ignore sunk costs, and are vulnerable to manipulation from affective triggers and complex pricing schemes. However, framing heuristics, biases, and other behavioral effects as simple errors or defects of our cognitive architecture ignores the evolutionary and cultural background in which these strategies arose.

At the foundation of behavioral economics is the notion of bounded rationality, as proposed by Nobel laureate Herbert Simon: that rational behavior suited to attaining an agent’s goals may be limited by various constraints—most notably the agent’s information-processing capabilities (Simon, 1972). While neoclassical economic approaches generally model decision-makers as having unlimited information processing abilities, real agents encountering a variety of decisions with limited cognitive resources encounter the need to make trade-offs between different decisions, and between decisions and action. Heuristics can be productively thought of as decision tools that allow for less effortful information processing than would be required to evaluate a decision exhaustively. By reducing the amount of evidence to consider, the complexity of the weighting process in applying evidence to a judgment or decision, and the number of alternatives to consider, heuristics can greatly reduce the cognitive effort of otherwise complex choices (Shah & Oppenheimer, 2008).

However, psychologists can easily construct scenarios in which heuristics backfire, sometimes with serious consequences. What, then, are we to make of their rationality? From the standpoint of ecological rationality, heuristics are rational in the sense that they “capitalize on environmental regularities to make smart inferences.” Because natural environments predictably present information in particular ways, highly specific heuristics can evolve to produce good results quickly and with minimal effort, provided that cues and problems are presented in the expected fashion. Accordingly, abstract representations like percentages are harder to process and lead to more error-prone probability estimates than more concrete
(and evolutionarily common) representations such as frequencies (Chase, Hertwig, & Gigerenzer, 1998). Because tasks and games in behavioral economic experiments are often presented in abstracted or unusual formats, a naïve reading of the literature may lead to an overestimate of the prevalence of irrational and maladaptive behavior in real-world situations.

To take one example, the winner’s curse describes how the winner of a common-value auction (in which bidders are uncertain of the value of the object being sold, such mineral rights of uncertain size) with many other bidders will tend to lose money: because each bidder’s estimate of the value of the item has a random error term, the bidder most likely to win the auction is the one with the highest estimate of its value. But since the highest estimate of the item’s value is likely to be an overestimate, winners may end up bidding more than the item is worth. This result has been verified in lab conditions among both students and professionals who bid on assets regularly. However, “given that construction firms participate in low bid auctions all the time, and would soon go bankrupt if they fell prey to the winner’s curse,” it appears that regular bidders learn a new set of heuristics that enable them to avoid (or at least minimize) the effects of the winner’s curse in the particular context of their livelihood, but do not successfully generalize to different environments (R. H. Thaler, 1992).

2.4 Applications of Behavioral Economics in Planning

A number of different practices within the field of planning today can be interpreted as implementations of the principles and findings of behavioral economics. Some of these practices are explicitly rooted in research from behavioral economics, behavioral decision making, or social psychology, while others were created from the insights of other academic fields, political or ideological principles, or simple trial and error in the field. However, organizing these practices as behavioral—that is, successful because of their application of evidence-based claims about human behavior—is a valuable exercise for multiple reasons. It illustrates the nascent interdisciplinary links from planning to behavioral fields and strengthens the
profession’s linkage to innovators in other disciplines. It helps to organize behavioral interventions as a distinct area of expertise in the planning profession, whose practitioners may have valuable contributions to make across the conventional subfields of planning. Most importantly, organizing the existing practice of behavioral interventions within planning may help suggest new applications of this body of knowledge to the challenges planners and their colleagues face.

2.4.1 A Framework for Practitioners

One attempt to sketch out a typology of how behavioral economics might be applied to public policy areas, including planning, is presented by Metcalfe and Dolan, who frame a set of techniques for influencing behavior through context with the mnemonic acronym MINDSPACE, and advocate using this set of techniques to address market failures resulting from uncaptured externalities (e.g. carbon emissions), inconsistent preferences, and inadequate or misinterpreted information in transportation decisions.

- **Messenger** refers to the importance of credibility, trust, and relatability of the individuals and organizations that deliver information on the costs and benefits of transportation options.
- **Incentives**, a traditional mainstay of behavior modification recommendations from economists, should be used cautiously, given the potential for extrinsic monetary rewards to ‘crowd out’ existing intrinsic motivations.
- **Norms** of culturally expected behavior are, by contrast, underappreciated as a method of changing behavior across groups; experiments have shown that, while many people expect their own behavior to change more in response to facts and information about the effects of their actions, their decisions are actually most strongly affected by information on the actions taken by peers.
- **Defaults** options can play a powerful role in influencing decisions; for example, rates of participation in retirement savings funds and organ donation programs can see large changes depending on whether they are constructed as opt-in or opt-out systems. The *salience* of
information relevant to a decision can change the way that it is processed, which may change the effectiveness of incentives and disincentives like taxation schemes.

- **Priming** effects—defined as an alteration to behavior following exposure to a particular stimulus—have the potential to change decisions in subtle but significant ways, although understanding how to do this in the field where many unknown factors may be exerting priming effects is challenging.

- **Affect** or emotional response plays a strong role in advertising and social marketing, and suggests that messaging that triggers either positive feelings (pride, happiness) or negative ones (disgust) can impact behavior more strongly than merely conveying objective information.

- **Commitment** can be leveraged in various ways (such as written contracts, self-imposed deadlines, and other commitment devices) to overcome procrastination and short-term decision-making.

- **Ego** impacts decision-making and evaluation through judgments that support a positive self-image. The fundamental attribution error (Miller and Ross, 1975) is a direct extension of this effect: we are more likely to attribute positive events in our lives to our own efforts or competencies, while failures and setbacks are interpreted as the result of situational factors or the behavior of others (Metcalfe & Dolan, 2012)

This toolkit of effects and considerations can help improve policy by increasing the practitioner’s ability to predict responses to incentives and information, improve the effectiveness of less coercive policies, and recognize biases and errors embedded in their own organizational procedures (Dolan et al., 2012). However, this still raises the question of when and where behavioral approaches are most promising, and when other modeling or policymaking approaches should be used. In the following sections, I discuss a few areas in planning where behavioral principles may be productively applied.
2.4.2 Transportation Pricing and Mental Accounting

The framework of mental accounting suggests that peoples’ aversion to holding accounts that are in debt may make prepayment plans a more attractive option than incremental payments, even when it raises the unit cost of consumption. Examples ranging from gym memberships (assessed on a monthly, not per-visit, basis) to phone and internet plans allow firms to make additional profits by selling not just their product but the ability to enjoy it without experiencing the unpleasantness of paying for each use. When given a choice between a purchase that must be paid for in cash up front and one that can be prepaid (through arrangements such as paying a flat rate for unlimited use of the item or paying with a pre-purchased token currency), people tend to consume more of the latter than they would have under the same payment scheme (Prelec & Loewenstein, 1998).

The various modes of personal transportation in cities differ in both their actual costs and benefits (price, time, convenience, comfort, etc.) and in the payment system that users must deal with. The contrast between driving one’s own vehicle and taxi rides is instructive: in the former case, the costs of driving are incurred infrequently and only occasionally align with a particular trip (e.g. weekly gas purchases, approximately annual insurance payments and license/registration fees, and vehicle purchases perhaps every five to ten years), a taxi ride involves paying for the trip immediately and attaching its cost to whatever activity the trip is made for. At the same time, many city-dwellers own an (additional) automobile that is used infrequently enough that the annual costs of ownership exceed the cost of replacing the trips it is used for with taxi rides, car rentals, or carsharing. The more salient pain of paying for these rides can result in “spending $8000 a year to own a car in order to avoid $4000 a year in taxis and car rentals”—a clearly suboptimal situation. Shafir and Thaler suggest that prepayment plans that allow users to buy rides or rentals in advance can reduce the added unpleasantness of hiring a cab or renting a car (Shafir & Thaler, 2006).
The principle can also be applied in the opposite direction through parking, demand management, and insurance policies. Any pricing scheme that creates a trip-level cost for the driver can be expected to increase the aversiveness of driving and encourage users to think more carefully about marginally useful trips. Reducing or eliminating the supply of free parking, increasing parking fees, and shifting parking pricing schemes to remove flat monthly rates and require drivers to pay for parking on a per-day or per-hour basis can make these costs highly salient for drivers, in addition to providing a variety of land use and congestion-reduction benefits (Shoup, 2005). Congestion pricing, such as programs introduced in London, Stockholm, and Singapore, further increase costs for users on a per-trip or per-day basis within designated routes or areas (Arnold et al., 2010). However, both of these schemes introduce new costs for drivers and may be politically controversial; by contrast, pay-as-you-drive schemes (PAYD) simply reassess existing insurance payments from an annual or semi-annual basis to a per-kilometer basis (Noel & Bordoff, 2008). In addition to the benefits of allocating the burden for risks incurred by driving in a more equitable way, it also makes insurance costs a more salient feature of each private automotive trip. By contrast, taxi, car rental, and carsharing schemes include insurance as part of a comprehensive fee; parking fees are irrelevant to taxi customers and a lesser concern for car share users, especially where designated parking for carshare users exists; and congestion fees could be waived or incorporated directly into the price of taxi fares and carshare fees.

Combining these approaches creates an opportunity to tip the balance of mental accounting factors in favor of carsharing, rental, and taxi usage. A program that allows users to pre-purchase plans corresponding to different usage scenarios and pay for them on a monthly, semi-annual, or annual basis greatly reduces the aversiveness of using automotive services that are costly on a per-use basis, while a system of different fees for auto usage, each of which are assessed individually and immediately, creates a number of small but salient losses that must be reckoned with on each trip in a privately owned vehicle.
Bikesharing systems currently in operation, such as Montreal’s Bixi and New York City’s Citi Bike, take advantage of this principle, offering daily, weekly, and annual passes that allow unlimited bicycle usage for short (<30-45 minute) trips (NY Bike Share LLC, 2013). However, because these systems charge users for usage beyond the specified time period, the prospect of being charged steep fees for additional usage due to unforeseen circumstances might still serve as a barrier to usage. If so, allowing users to prepay into an account for such purposes might help eliminate this obstacle to joining the program.

A similar logic can be seen in the prevalence of prepaid options for transit users, such as buying fare tickets in prepaid bundles or for daily, weekly, or monthly unlimited-use passes. These options reduce or eliminate the salient unpleasantness of paying a fare for each transit trip taken and are a good strategy for maintaining the attractiveness of transit services for existing riders and those who are automatically enrolled in unlimited pass systems, such as university students (Senft, 2005). However, the up-front cost of transit use may serve as a barrier for experimentation by potential new users; even potential passengers for whom a typical transit fare of $2 to $5 is a minor expense may balk at an upfront price when automotive trips are perceived as free. The mental accounting framework suggests that one solution to this obstacle is to provide ways for new users to pay using the same account or payment stream they already use for other transportation services. For example, integrating transit fare collection with payment mechanisms for other services, such as vehicle rental/hire or bikeshare systems, may reduce the extent to which new users experience an aversive expense associated with transit use and increase opportunities for people to experiment with various combinations of non-automotive modes.

2.4.3 A Behavioral View of Opposition to Market-Based Solutions

Economists agree almost universally that congested roads ought to be subject to some kind of pricing scheme. While disagreement exists on important details of implementation and administration—how fees should be collected, whether certain users should be granted discounts, and how revenues should be spent—a strong professional consensus exists in favor of congestion pricing schemes (Lindsey, 2006).
Furthermore, evidence from a 2006 referendum on the adoption of congestion pricing in Stockholm, Sweden demonstrated that initial opposition to the program faded after users experienced its monetary costs and travel time benefits firsthand: the referendum to maintain the policy passed with 52% in favor (Hársman & Quigley, 2010).

In spite of evidence from both economic theory and empirical results of practical trials, many economists remain pessimistic that congestion pricing will see widespread adoption in the foreseeable future. One reason that has been suggested for this is the notion that individuals are likely to lose out when market solutions are implemented:

“In the words of a Dutch proverb, ‘He who has choice has trouble.’ Psychologists use the term ‘agoraphobia’ for a psychosis that means, literally, fear of the marketplace… most consumers display some degree of agoraphobia in their attitudes towards markets and market solutions to problems of resource allocation, distributed markets and their own decision-making ability” (McFadden, 2007).

McFadden outlines a variety of reasons from the behavioral economics literature for why people with insight into their own susceptibility to errors in decision-making may reject market solutions, even if they comprehend the underlying rationale of the policy. He notes that loss aversion may make the results of mistakes and costs borne while adapting to a new system loom larger than the policy’s gains, especially when those gains are uncertain, diffuse, or may not take place until some time into the future. In addition, adapting to market mechanisms involves cognitively demanding trading activities, and people “may legitimately fear that lapses in memory, reasoning, or understanding of the choice process and their own goals will put them at a disadvantage relative to skilled traders” (McFadden, 2007). Bringing well-supported market solutions to transportation and planning problems is therefore best understood not only as a problem of applying conventional economic reasoning to policy design, but also of applying
behavioral decision research to predicting and educating peoples’ attitudes as consumers and political actors.
3. A FRAMEWORK FOR NUDGING IN ACTIVE TRAVEL PROMOTION

3.1 Who Benefits from Active Travel Promotion?

Historically ignored and underserved by the transportation profession, cycling, walking, and other active modes have been rediscovered as practical, sustainable, and health-promoting modes of transportation. Encouraging more people to walk and cycle more frequently to work and other destinations can decrease vehicular congestion and costly infrastructure needs, promote better physical fitness and cardiovascular health, reduce demands for fossil-fuel derived energy, and cut greenhouse gas emissions and harmful pollutants.

The range of benefits that active transportation can provide has made investments in enabling cycling and walking an attractive option for a diverse group of stakeholders: employers with healthcare liabilities, environmental agencies charged with reducing emissions and pollutions, transportation service providers seeking to reduce infrastructure and maintenance costs, and planners and policymakers seeking to create more vibrant, interesting public places while reducing congestion and gridlock. Additionally, stakeholders such as local business associations and persons who are unable to drive for reasons of age or disability also stand to realize substantial practical benefits from communities that acknowledge the importance of active transportation.

While many groups stand to benefit from greater adoption of active modes, the diffuse nature of these benefits can make active travel promotion a low-priority item for many of these organizations. Policymakers in municipalities, regional governments, and transit agencies may have more pressing priorities, little institutional capacity to conduct community-based marketing efforts, and political disincentives against explicit efforts to change peoples’ transportation choices. Employers and businesses
may see shifting transportation modes as too small a concern or too difficult a challenge to be worth crafting policies or incentives. Larger agencies, such as state, provincial, and national transportation and environmental protection bureaucracies, are often too remote from local communities to undertake effective or relevant promotional efforts, and may also face difficulties in assessing the results of interventions that don’t produce directly measurable results: a bike path, for example, can be judged by the number of users that it attracts, but disentangling ‘natural’ growth in cycling from those attracted by a promotional campaign may be impossible.

Because of these barriers, efforts to actively promote bicycling and walking in North American cities can be a difficult fit for many of the institutions that stand to benefit from them. However, a particular kind of group exists that fits this niche well: the active travel advocacy group (hereafter “ATA”). The most common and visible form of ATA is the bicycling advocacy group, with a history stretching back to the formation of the League of American Wheelmen (LAW) in 1880. Initially formed to advocate for paved roads before automobiles made them a necessity, organizations like the LAW’s modern incarnation, the League of American Bicyclists, have seen their role shift to include educating new cyclists, training instructors, lobbying for transportation funding for bicycle infrastructure, and promoting cycling through events and marketing (Sturges, 2013). Similar groups with a national profile in the United States include the industry-sponsored Bikes Belong and the Alliance for Biking and Walking, which includes advocacy for walkability in its portfolio as well. In addition to these national-scale groups, over 200 North American organizations are involved in advocacy for bicycling and walking at a local or regional level.

As a result, active transportation advocacy groups (hereafter “ATAs”) may be the sole or primary group in many communities putting significant efforts into promoting cycling and walking to work. Because of the funding constraints these groups tend to experience, they often have small or non-existent full-time staffs and are heavily dependent on volunteers and community partners to run events and other programs. While many ATAs manage to consistently run successful, popular, and effective promotional campaigns,
their capacity constraints may prevent them from collaborating between organizations to share findings and strategies, experimenting with innovative possibilities for their programs, or accurately assess the impacts of their efforts.

### 3.2 A Model for Advocacy and Research

An ideal framework for transforming ATAs into more effective promoters of cycling and walking would have several characteristics: it would help both advocates and transportation researchers study the outcomes of different programs; enable the development of best practices for active transportation promotion; and facilitate collaboration between ATAs and other stakeholders by improving their capacity to communicate their results and demonstrate how their programming aligns with outside interests. It should be lightweight to implement and administer, requiring limited resources and training. All of these characteristics would increase the ability of successful ATAs to demonstrate their value to different potential partners, and attract funding and other resources to expand their most successful programs; it would also empower advocacy groups struggling with limited successes to learn from evidence-based best practices and increase the effectiveness of their programming.

A three-component framework of mobile applications, behavioral nudges, and randomized control trials can together provide a program that meets these criteria while providing a powerful platform for research on transportation behavior, creating valuable knowledge for both academics and practitioners. Together, these tools allow ATAs and researchers to accurately gather data on peoples’ travel behavior in an accurate, objective, and unobtrusive way; provide feedback and communications that encourage people to choose sustainable modes using proven communications techniques; and rigorously test a variety of different approaches to determine the most effective programs and marketing strategies. Below, we examine each of these components in greater depth and describe their role in this strategic framework.
3.2.1 Mobile Applications in Transportation

In the past, the tools for transportation planners and advocates to measure how people travel have been constrained by a variety of practical challenges. Some conventional tools that researchers have used to examine travel patterns, such as surveys and travel diaries, rely on participants to accurately describe their own mobility over the course of one or more days. This is often an unrealistic assumption, and evidence suggests that respondents may not correctly report short, infrequent, or complicated trips, and may do a poor job of estimating the distance or duration of their journeys (P. Stopher, FitzGerald, & Xu, 2007). An activity-based approach can overcome some of these limitations but is still subject to important constraints, including reliance on accurate, unbiased, and diligent data recording by participants, time delay between the travel activity being measured and when the data is available to the researcher, and difficulty establishing patterns of activity within participants without a long and burdensome study (Schlich & Axhausen, 2003; P. R. Stopher, 1992).

Other methods, such as traffic counts, can provide an accurate picture of how travel patterns at large change over time, but it can be difficult to distinguish between different kinds of behavior change. A decrease in traffic on a major highway might indicate that fewer people are driving, or that more people are driving via other routes, and absent a comprehensive set of counts it can be difficult to determine how behavior has changed. It also can be difficult to measure demographic characteristics of travelers with manual traffic counts, and impossible with automated methods such as loop detectors (Leduc, 2008).

In studies of active travel, especially those conducted in the public health field (see e.g. Cooper et al., 2006), issuing devices such as pedometers, activity meters, and GPS bicycle trackers to travelers can produce detailed data on their levels of activity, including transportation such as walking and cycling. This approach has the advantage of removing the need for people to estimate their own travel, giving researchers a more precise and objective measurement of how much a person walked, cycled, and was active over the course of their day (Frank et al., 2005). However, this method presents significant
challenges: the hardware needed to run this sort of trial on an adequate sample size can be quite costly, and the meters must be mailed or delivered to participants, adding additional overhead for shipping or distribution. Additionally, these devices may not be able to distinguish between different trips and different kinds of exercise, making it impossible to determine whether a burst of activity is a bike ride for an errand (potentially replacing an automotive trip) or an episode of recreational exercise.

All three of these methods entail substantial costs for any study that aims to gather a large sample of data on mobility within a group or geographical area, whether through purchasing equipment such as accelerometers; paying observers, interviewers, or coders; or providing monetary incentives to participants. In the future, better options for automated data collection may become prevalent: for example, smartcard data from public transportation systems may allow researchers to examine individual activity in great detail over long periods of time. However, this method is limited in scope to trips via public transportation, making it highly appropriate for public transport network optimization, but less useful in understanding comprehensive travel patterns of individuals or households across modes (Bagchi & White, 2005). Privacy concerns may prevent that information from being matched against data sources from other modes, limiting its usefulness for active transportation advocates. Additionally, substantial data-management and analysis infrastructure is necessary to manage the datasets produced by this method, involving both data mining and transportation expertise (Agard, Morency, & Trepanier, 2007).

In contrast to these methods, mobile applications for platforms like Android and iOS have a variety of capabilities uniquely suited to detailed measurement of active travel. These apps can track individual travel via a combination of GPS location and accelerometer readings, accurately determine when and where a person is travelling, and distinguish between walking, cycling, and motorized modes. They have the capacity to recognize even short trips, such as from one part of a workplace to another, and to create records of when, where, and how a person has traveled. In addition to providing the commuter with a record of their travel behavior, it also allows users to share their information with other individuals.
(friends, family, and coworkers) or organizations (ATAs, researchers, transportation agencies). Two examples of this type of app are ProtoGeo’s *Moves* (ProtoGeo, 2013) and *Quantified Traveler*, developed by a team at UC-Berkeley (Jariyasunant et al., 2011).

Discussing GPS tracking systems, Wolf *et al.* note that the “potential advantages of using GPS […] are numerous: 1) trip origin, destination, and route data are automatically collected without burdening the respondent for the data; 2) routes are recorded for all trips, allowing for the post-processing recovery of unreported or misreported trips (including linked trips); 3) accurate trip start and end times are automatically determined, as well as trip lengths; and 4) the GPS data can be used to verify self-reported data” (Wolf, Guensler, & Bachman, 2001).

A key advantage of an app-based approach is that while it provides the same strengths as a dedicated GPS instrument, it does not require researchers or organizations to invest in any monitoring hardware, and apps for this sort of data collection are commercially available or could be developed with an organization’s specific needs in mind and used for many years thereafter. The app can be distributed at zero marginal cost to a large number of participants, whose travel behavior can be recorded with little or no user effort. This enables advocates or researchers to gather data over a longer span of time than would be feasible or cost-effective using other methods; for example, an organization might be able to monitor how fluctuations in temperature and weather affect the same group of cyclists over the course of a year.

From the participant’s perspective, the primary burden of participation is in the signup and app installation procedure. Depending on the structure of the app, data may be retrieved from participants either by a manual procedure (emailing data or filling out a survey) or through an automated method (through the app itself or scripts interfacing with an app API). Non-participation or attrition might occur as a result of difficulties obtaining or installing the app, technical problems with the app, or user burden from manual data transmission procedures; however, the day-to-day burden of this procedure will likely
be substantially lower than self-reported methods, and comparable or lower than dedicated activity-measuring devices.

In the future these methods might also be able to capture travelers’ use of public transportation and private automobiles as separate modes, although this capability has not yet been implemented with a high degree of accuracy in available apps. Integration with transit schedules or real-time location tracking might help to lessen the difficulties of distinguishing between modes based only on accelerometer and location data. Apps might also serve as platforms for two-way communication between advocates or researchers and the end user, allowing customized in-app messaging to be sent to users based on their travel patterns. In addition to the behavioral feedback programs discussed below, ATAs might also distribute travel advisories, safety tips, or information on community events for cyclists and pedestrians.

3.2.2 Behavioral Nudges

Over the past several decades, psychologists and behavioral economists have developed a sophisticated understanding of the ways in which many economic decisions—including location and transportation choices—differ from the idealized rational actor models of mainstream economics. They discovered, for example, that people respond to outcomes using different standards, depending on whether they are presented as losses or gains (Kahneman & Tversky, 1979); that choosing between a large number of options can be cognitively overwhelming and result in less satisfaction with the choice than if it were made between a smaller number of possibilities (Iyengar & Lepper, 2000); and that people often choose differently depending on whether the same situation is perceived as governed by market norms or non-market social norms (Gneezy & Rustichini, 2000). As the field developed, many of the effects and techniques they discovered and systematized—some of which had been part of marketers’ arsenals for decades—found a new life in crafting policy.

2 The methods and findings of behavioral economics are discussed in greater detail in Chapter 2.
This approach was popularized by Richard Thaler and Cass Sunstein in their popular book, “Nudge: Improving Decisions about Health, Wealth, and Happiness,” who advocate an approach to public policy called libertarian paternalism. When people seem to consistently make choices that result in poor individual or social outcomes, they argue, designing the context of their choice in a way that nudges them towards a decision that will produce a better outcome in most situations is often effective and justifiable. They note, for example, that many people fail to make beneficial decisions about saving for retirement because the default, “do-nothing” choice presented by an employer is often to save nothing. Intervening to reduce the burden of this decision by making a choice of savings rate and investment portfolio that will likely be optimal for most people in most circumstances preserves employees’ freedom to manage their money however they see fit, but ensures that those who procrastinate or lack the time to make an informed decision will avoid predictably bad outcomes (R. Thaler & Sunstein, 2008).

One domain in which this approach has been successfully applied is in efforts to promote household energy conservation. Many electric utilities have legislatively-mandated greenhouse gas emission reduction targets, which can be accomplished in a number of ways. One of the most cost-effective methods is to simply reduce the amount electricity that end users consume. Organizations such as OPOWER have borrowed techniques from behavioral economics in order to frame energy consumption not just as a purely economic decision, but also one that is governed by social norms of sustainability and conservation. By showing people how their energy use compares to their neighbors’ alongside tips for decreasing unnecessary consumption, OPOWER has found that households randomly assigned to the program used around 2% less electricity each month than comparable controls (Allcott, 2011). The program is easy to scale up, highly cost-effective compared to other alternatives, and has resulted in cost savings for participating households totalling over $300 million (OPOWER, 2013).
Many of the ways in which people make decisions about how to travel are similar to how they make choices around energy consumption: both are often heavily embedded in our routines, and people often make day-to-day decisions based simply on convenience. This suggests that interventions that make certain travel decisions more salient or highlight the costs of an auto-dependent travel routine may be effective in changing behavior where purely monetary incentives fail or aren’t politically or practically feasible.

ATAs (as well as transit agencies, municipalities, and employers) might implement insights from behavioral economics and lessons from successful behavioral interventions like OPOWER across a variety of different messaging and programming venues: bike to work programs, school- and family-based bicycle promotion and education events, seasonal active transport challenges, bike-friendly business programs, and advertising and awareness campaigns. Some of the tactics that might be effective include increasing the urgency of adopting active travel behavior by framing non-use of active modes as a loss (of health or money); motivating active travel by creating social comparisons between users and invoking a sense of competition; establishing new norms and defaults around transportation behavior; matching different kinds of interventions to specific values or priorities that users are motivated by, based on demographic characteristics or other sources of information about participants; and using the affect heuristic in messaging to reinforce and lock-in sustainable changes in behavior.

3.2.3 Randomized Controlled Trials

Mobile apps give researchers a means of measuring travel behavior more accurately and unobtrusively than was previously possible, while behavioral decision research provides a rich source of hypotheses about mechanisms for modifying behavior and increasing the effectiveness of active transportation promotion efforts. Given these new possibilities, the third element of a successful research program and evaluation strategy is a means of measuring the effectiveness of different interventions. Randomized
controlled trials (RCTs) provide a rigorous way to conduct performance evaluations and provide accessible and compelling evidence of the results of different interventions.

Randomized controlled trials have a rich history in medicine and have seen increasing use in fields including international development and e-commerce (Haynes, Service, Goldacre, & Torgerson, 2012), as well as limited applications within the transportation profession (Graham-Rowe, Skippon, Gardner, & Abraham, 2011). By randomly dividing participants into control and test groups, researchers can compare the outcomes associated with different interventions without, as in other study designs, the possibility of underlying differences in unobserved characteristics exerting an influence on outcomes. Randomization will normally take place at the level of individual users, but a program manager might also randomize which groups receive different treatments at the level of workplaces, schools, or neighborhoods. This approach will generally require more users in order to do an accurate test, but can provide the ability to test the effects of interventions that operate on a community level. For example, an organization that would like to test the effectiveness of distributing rankings of all users’ behavior within an office would be better served by randomizing at the workplace level instead of the individual level.

Randomized controlled trials have traditionally been viewed as expensive and time-consuming to run, but this is no longer true in many cases (Haynes et al., 2012). Free or cheaply available survey software and database systems can easily randomize users into different groups when they register to participate in ATA programs and activities. Based on these random assignments, different interventions can be given to participants. Apps, as well as surveys and other feedback mechanisms, can provide data on outcomes, such as how frequently participants are using active modes of travel.

Within the transportation field, existing work provides several examples of the potential of behavioral nudging, as well as the use of randomized controlled trials and similar study designs. Perhaps the most useful compilation of lessons on study design available is a review article of 77 studies of transportation
emissions reduction programs conducted by Graham-Rowe et al. Of these 77 studies, six were summarized as high-quality (randomized controlled trials, quasi-experimental designs, or controlled pre/post cohort analyses) studies that included a psychological intervention approach (Graham-Rowe et al., 2011).

One study that combined monetary incentives with an auto trip reduction plan was effective at decreasing trip distance and frequency, while a similar study based on providing information to commuters was not effective at reducing automotive trips. Of the four studies that tested purely psychological approaches (based on information, feedback, commitment, and planning interventions), two were effective at reducing automotive trip frequencies, a third was ineffective at reducing automotive trip frequencies, and the last study was ineffective at reducing total vehicle kilometers traveled. Of the 77 studies considered in this review, only 12 were classified as “high-quality” analyses that implemented rigorous and well-controlled evaluation procedures, and two of the 12 had very small (n < 25) sample sizes conducted in unrepresentative populations (e.g. university students).

Among studies that were evaluated as less methodologically rigorous, results tended to be more favorable towards ‘nudging’-style interventions. Of the additional 14 “medium-quality” analyses that employed uncontrolled cohort studies, 12 examined psychological interventions. 11 of these studies reported positive results of their interventions, with the 12th reporting positive results at one of two worksites studied.

This review has at least two relevant implications for our research program. First, the more mixed results seen from randomized controlled trials implies that these more rigorous trials have a better chance of identifying ineffective programs than less methodologically sound study designs. This is a valuable trait, because it implies that the chance of a study producing a false positive are lower and allows for more confidence that positive results reflect truly effective interventions. Secondly, the small sample sizes in
the studies examined here (ranging from dozens of participants to approximately 1300 at the high end) indicate an opportunity for ATAs with large-scale promotional programs (in some cases drawing tens of thousands of registered participants) to contribute to the literature on behavior change in transportation with large, fine-grained, high-quality datasets that implement randomized controlled trials on a larger scale than in prior research.

3.3 A Typology of Behavioral Interventions in Active Travel Promotion

Under the umbrella of this approach, researchers and practitioners can test a large number of different interventions designs, varying across many dimensions. Because interventions can be delivered using a variety of mechanisms, schedules, timescales, and levels of detail and specificity, it is not practical to test more than a very small set within the large space of possible experiments. By sketching the dimensionality of this space and suggesting a sample of promising possibilities, we hope to guide future investigations and narrow the set of parameters for researchers and practitioners designing interventions along these lines.

3.3.1 Parameters for Behavioral Intervention Design

Variables that must be considered in this type of study include:

Platform and Automation: the most important variable to consider in designing an app-based behavioral intervention is how the data is to be gathered, transferred to the research team, and converted into feedback reports for the user. Ideally, the app should gather accurate data on all modes of transportation the user engages in (both active and motorized), transmit it to the research team or program manager with no active effort required from the user, allow automated or minimally effortful data processing and generation of feedback reports, and distribute feedback to participants in a streamlined, user-friendly manner. The platform should also provide flexibility in assigning participants to different experimental groups and providing them with different interventions. However, no platform with all of these features
currently exists, requiring practitioners and researchers to make trade-offs between the features of the systems available.

**Data Types:** data can be collected from respondents at varying levels of detail, ranging from highly abstracted summaries of daily, weekly, or monthly activity (e.g. total time and/or distance for walking, cycling, and motorized transportation); trip-specific metrics such as times, durations, and distances; or moment-by-moment location and travel mode data throughout the day. At the most abstracted level, sufficient data to track aggregate changes in behavior can still provide significant and valuable information on the effectiveness of programs, but more detailed data allows researchers to understand mobility patterns in greater depth by e.g. identifying differences between journey-to-work and discretionary trips. At the greatest level of detail, locational data can allow imputation of trip purposes, as well as providing data on the built environment and transportation infrastructure encountered by the user. However, higher levels of detail requires greater data storage and processing capacity, more robust security measures, and more stringent policies to protect user privacy.

**Duration:** the appropriate duration of a behavioral intervention can vary substantially. Should it be the same as a promotional effort (e.g. a week, month, or season aligning with a bike-to-work initiative), continue for a predetermined length of time after a promotional effort, or continue indefinitely? The answer to this question may depend on user motivation, researcher data needs, and the availability of resources to run a long-term experiment.

**Frequency and Timing:** researchers must determine how often to collect data and provide users with behavioral interventions such as feedback reports. Daily, weekly, biweekly, monthly, bimonthly, or seasonal reports are all feasible to implement in a program with automated data collection, so researchers or program managers must test or make judgment calls regarding the optimal frequency of interventions. If data collection is not automated and requires user effort, daily data collection may be too burdensome,
but the rest of the options remain feasible. In the case of more frequent intervention schedules, timing may also be an important factor; reports could be issued in the late afternoon (near the end of the workday), early evening, late evening, or in the morning before the commute. This forces the researcher to consider when a feedback report is most likely to influence a user’s mode choice on their next commute.

**Background Information:** in addition to gathering data from users’ mobile apps, questionnaires can be used to gather data from users on a variety of demographic, attitudinal, and behavioral characteristics. In addition to basic questions such as age, gender, income, household structure, and baseline frequency of active travel, a variety of other pieces of information may be useful in determining the effectiveness of different interventions. Of particular interest are variables that might predict users’ reactions to different types of feedback, including beliefs and concerns about the environment, their health, or their finances.

**Data Presentation:** data can be presented to users in many ways, requiring researchers to answer a number of questions about data visualization strategies. Are simple bar and pie charts and trend lines the most direct way to communicate data about a user’s commute, or are other visualization techniques more effective? Should feedback reports emphasize quantitative data, qualitative evaluations, or a mix of both?

**Impact Metrics:** users can be provided with measures of the impact of their mobility patterns, such as greenhouse gases (emitted by automotive trips or avoided by non-motorized trips), calories burned, or money saved (by avoiding incremental costs of automotive or transit trips). Research is required to determine which metrics have the strongest impact on user behavior, whether providing several metrics is more effective than a single metric, and how impact metrics should be contextualized. Additionally, interventions could be designed to provide different types of impact metrics to users based on demographic characteristics, values, or political views. In a study of OPOWER’s impacts on households of different political leanings, significant differences were found between environmentalist Democratic
households, which were found to respond to the intervention with a 3% decrease in electricity consumption, and non-environmentalist Republican households, which responded with a 1% increase in electricity consumption (Costa & Kahn, 2010). The potential for behavioral nudges that appeal to politically charged values to backfire among certain groups suggests that targeting different values among different audiences may enhance the effectiveness of the overall program.

*Feedback Mechanism:* feedback can be communicated to users through several channels. Researchers or program managers working with less integrated techniques, such as manual data entry to a survey form, will naturally default to using email as a means of communicating feedback reports. However, a more fully integrated app platform may be able to deliver feedback through app notifications, text messages, or other formats.

*Social Comparisons:* behavioral research indicates that social comparisons can be powerful motivators for behavior change (Ashby et al., 2012; Frey & Meier, 2013), and app-based data collection allows researchers to provide users with a number of comparisons against different reference groups. Users’ commute and impact metrics can be compared against national, state, provincial, or local averages; broad or narrow groups of fellow app users; fictional characters exemplifying desired thresholds of activity; or tailored or self-selected groups of friends, family, or coworkers. Comparisons can be framed as either purely informative or as a competition, and can be made at either the individual or the group (e.g. workplace or household) level.

*Social Network Integration:* activity tracking apps may be able to integrate with a user’s social network profile and activity, providing a number of opportunities for researchers and program managers to gather additional information, and for users to share and compare information about their commute with others. Of particular interest is the capability to compare the behavior of different members of the same household or workplace and make inferences about social influences on travel behavior within these
groups. However, integration with social media creates additional burdens for the researcher or program manager to ensure that privacy and data security policies are sufficient to protect both their users and their organizational reputation.

3.3.2 Example Interventions

The many dimensions along which trials can vary create a very large number of theoretically possible interventions. However, several particular combinations present themselves as promising:

- **Minimal Intervention**: to understand the baseline impact of merely providing feedback to users on their commuting behavior in an impartial way, a test comparing users receiving no feedback at all with those receiving only neutral feedback, such as their aggregate statistics and impacts. This intervention can provide a benchmark for determining the added value of behavioral interventions in other systems.

- **Social comparison and emotional cue**: the household energy reports (HERs) provided by OPOWER provide an example of current practice in another domain, and use impact statistics, comparisons against neighbors, and an emotional cue indicating whether the user’s behavior meets a normative standard.

- **Positive reinforcement**: in addition to the ‘social comparison and emotional cue’ intervention, sending users short and encouraging messages via email or in-app notifications immediately after recording an active trip may help to create a strong link between the desired behavior and app feedback.

- **Competition**: team-based competitions may be able to recruit social norms more strongly in support of consistent active travel behavior, suggesting that a feedback report that scores both individual behavior in relation to a workplace group’s overall performance, as well as the workplace group in comparison to other groups, may create good results. This competitive framing has been used in existing active travel promotional systems, such as greenlightride.com.
• **Social Network Integration:** in addition to the ‘social comparison and emotional cue’ intervention, allowing users to designate other users (such as family members, friends, or coworkers) to share their travel and impact metrics with may create more informal sorts of competition, as well as allowing the researcher to examine whether users are influenced by the behavior of other active commuters in their social network.

• **Targeted reinforcement:** the ‘social comparison and emotional cue’ intervention is made more user-specific by asking users a small set of questions designed to measure their environmental values, health-consciousness, and fiscal prudence, and only presenting impact metrics that match the user’s areas of interest. This approach may increase motivation by removing information that users perceive as irrelevant to their values or concerns, but also may miss opportunities to increase user awareness about these issues.

• **Gamification:** combining the ‘positive reinforcement’ and ‘social network integration’ interventions could result in a feedback system that uses many principles of *gamification*, defined as the process of “us[ing] video game elements in non-gaming systems to improve user experience and user engagement” (Deterding, Sicart, Nacke, O’Hara, & Dixon, 2011). By matching user behavior with a variety of reward, reputation and competition mechanisms, user motivation might be substantially increased.

### 3.4 Benefits and Limitations

Using this system, active travel advocates have a greatly expanded toolkit for improving their programming, learning from each other’s programs and experiments, and demonstrating concrete results to potential partners and funders in other organizations. When a randomized controlled trial on an active travel strategy has been completed, the results will allow researchers to understand not just whether or not the intervention they tested has an effect, but also to estimate how large the effect is and the cost-effectiveness (e.g. dollars per additional active trip or per unit of emissions avoided).
App-based data gathering also gives ATAs the ability to track the impacts of their programing over long periods of time. With this capability, ATAs can track cycling behavior for months or years and determine the long-term effect of participating in a given program. By setting a defined and objective measure, such as active trips per month, as a common standard, ATAs can compare across both their own programs and other organizations’ strategies to identify the most cost-effective solutions in their own portfolio as well as promising interventions developed elsewhere. This evidence can provide an objective and easily comparable standard for policymakers and funding agencies with a mandate to allocate resources towards different strategies for sustainable and health-promoting transportation. It also provides a standard for evaluation and testing new programs against existing approaches.

An important caveat for evaluators and researchers to keep in mind is that RCTs operate on the condition that the only factor that varies across the study is the treatment being tested, and that subjects in the control group are isolated from its effects (Haynes et al., 2012). In an active travel promotion context, this assumption may not be true. Users in one group might compare their reports with those from another, exposing them to the messaging approach being tested. This could potentially increase or decrease the desired behavior in the control group, depending on how the discrepancy in messaging is interpreted. A related implication is the fact that users in the test group may become more likely to take advantage of other programs that promote and enhance active travel, whether offered by the ATA or other organizations. Because resulting changes in behavior are partially attributable to programs other than the intervention being tested, an RCT demonstrating an effective strategy may not be fully generalizable to contexts in which the same promotional efforts or bike-friendly policies are not present.

Another important limitation of this approach is that individuals who do not own smartphones cannot participate in either the behavioral intervention or program evaluation components of this strategy. In the United States, smartphone ownership is estimated at 56% of the adult population. Because of this
limitation, people who may stand to benefit most from active travel promotion may not be able to benefit from this intervention approach, including low-income individuals without the financial resources to pay for an advanced phone and data service, older adults who are not as technologically literate, those with vision or other impairments, and those who live in rural areas with no or limited cellular data service (Smith, 2013). Additionally, this approach has limited applicability to school-based programs that target behavior change messaging at children. Although children may carry smartphones, their limited prevalence among younger schoolchildren as well as heightened privacy and security concerns will likely prevent app-based interventions with minors. Because many of these limitations in data-gathering coincide with groups who may face other barriers to making active transportation part of their routine, undersampling of these groups might lead to the false impression more widespread applicability than an intervention has among the overall population.
4. BEHAVIORAL INTERVENTIONS USING MOVES: TWO PILOT STUDIES

4.1 Introduction

In order to test the feasibility and effects of app-based data collection and behavioral interventions, we conducted two randomized controlled trials to test different intervention styles, participant groups, data processing methods, and institutional contexts. We conducted pilot trials of these two designs, the results of which are reported below. Two additional trials have been designed and will be launched in late 2013 as technical capabilities are developed and new partnership opportunities become available; these designs are discussed in greater detail in Chapter 5.

The two experiments presented in this chapter are as follows:

1. *University of British Columbia Pilot*: we tested a preliminary experimental design in a university setting on a sample of graduate students at the University of British Columbia. Control participants received basic feedback reports, while test participants received additional comparisons and an emotional cue. 17 students were recruited, of whom 7 (41%) provided data. While the data from this pilot was insufficient to test the effectiveness of our interventions, this initial test allowed us to identify potential difficulties with our approach prior to implementing at a broader scale.

2. *Bike to Work Week Pilots*: we tested an improved design with participants in three June and July 2013 Bike to Work Weeks events held by active transportation advocacy groups, including Bike to Work BC, HUB Vancouver, and Twin Cities Commuter Connection. Control subjects received basic feedback reports, while test subjects received additional comparisons, an emotional cue, and a prompt to set active commuting goals. 70 participants were recruited, of whom 35 provided data. The data gathered in this pilot did not produce significant associations.
between active travel and our interventions, qualitative information demonstrated a high degree of user satisfaction with the app and interventions, as well as providing more detailed insight into the strengths and weaknesses of our data-gathering approach.

Table 1: Comparison of Experiments

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Methods</th>
<th>Interventions</th>
<th>Population</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. UBC Pilot</td>
<td>Manual entry and report creation</td>
<td>Weekly basic vs. weekly enhanced feedback</td>
<td>Students, moderately motivated</td>
<td>Recruited: 17 N = 7 Duration: 4 weeks</td>
</tr>
<tr>
<td>2. BtWW Pilots</td>
<td>Survey-based entry and automated report creation</td>
<td>Weekly basic vs. weekly enhanced feedback with goal prompt</td>
<td>Bike to Work Week participants, highly motivated</td>
<td>Recruited: 70 N = 35 Duration: 4 weeks</td>
</tr>
<tr>
<td>3. MTurk Experiment</td>
<td>Fully automated entry and report creation</td>
<td>No feedback vs. weekly enhanced feedback and goal prompt</td>
<td>MTurk users, self-selected but not necessarily highly motivated</td>
<td>Target N = 250 Duration: 4 weeks</td>
</tr>
<tr>
<td>4. TC Experiment</td>
<td>Fully automated entry and report creation</td>
<td>Monthly feedback vs. weekly enhanced feedback and goal prompt</td>
<td>Bike to Work Week and rideshare program participants</td>
<td>Target N &gt;= 100 Duration: ongoing</td>
</tr>
</tbody>
</table>

4.2 Overall Methodology: Activity Tracking and Feedback Method

4.2.1 Mobile Platform: Moves App

Our platform for this study was Moves, an activity tracking app developed by Finnish developer ProtoGeo and available as a free download, as of this writing, for iOS devices, including all generations of iPhones. Moves uses a combination of location-detection methods (including GPS, cellular networks, and WiFi signals) and accelerometer data to detect the user’s modes of transportation over time. It can distinguish between motorized transportation (including automobile, taxi, and public transit), cycling, walking, and running, and provides data on the user’s time and distance spent using each of these active modes; trips are automatically tracked at any time the user’s phone is on without requiring any action on
the part of the user. Users can view their activity on a daily or weekly basis; at the daily view, the user also has the option of viewing an activity record of their locations and trips throughout the day, and can designate and label (e.g. as “Home” or “Work”) geographical points at which they’ve spent time (ProtoGeo, 2013).

Compared to other activity tracking applications on the market, Moves has several advantages: it allows for tracking with minimal user effort, taking advantage of passive monitoring systems that can detect when activity begins and ends with reasonable accuracy while minimizing battery drain when the user is not traveling. Judging from our own tests and user experiences, the app provides fairly accurate discrimination between different modes and can reliably detect short trips (<5 minutes), including active travel to and from transit stops. The app can process and display this information in near-real-time, allowing users to monitor their activity throughout the day through a simple and attractive user interface. An additional capability of the Moves app that promises to improve functionality on the researcher side is the application programming interface (API) available to developers for querying Moves servers directly. Our application of this capability is discussed in greater detail in Chapters 5 and 6.

One disadvantage of the Moves platform is that, as of this writing, the app is available only for iOS devices. (A version of the app for the Android mobile operating system is in progress and has limited availability for alpha testing, but is not currently available on the Google Play store, the primary distribution channel for Android apps.) At the time of this set of trials, iOS devices hold a 39.2% market share among all smartphones in use (Flosi, 2013). With 56% of adults in the United States owning a smartphone, this implies that approximately 22% of contacted users would be able to participate. However, variability in smartphone ownership is significant: younger, higher-income, urban and suburban, and more highly educated populations all tend to own smartphones at significantly higher-than-average rates. For example, smartphone ownership is estimated at 90% among 18-29 year olds with
household incomes over $75,000, and among smartphone owners as a group, the iPhone’s market share is greater among those with higher incomes and educational attainments (Smith, 2013).

4.2.2 Data Collection and Feedback Format

Respondents provided us with the data collected by the Moves app with one of two methods. In the first trial, participants sent data directly from the app, which allows users to easily send graphical weekly activity summaries of their walking, running, and cycling via email, with units given in distance. We requested that users send the research team these summaries each week, which were manually entered into a database. In the second trial, we instead asked participants to submit activity information to us via a short online survey that asked them to copy their weekly time spent walking, running, and cycling from the activity summary in the app. Participants were sent this survey via a scheduled email each Sunday evening.

The online survey method removed the need for manually copying activity measures from user reports and instead allowed us to use a Python-based script called EasyFeedback (detailed in section 6) to collect and manage participant data, generate feedback reports, and distribute reports to participants via email.

Feedback was provided in the form of a one-page report summarizing the participant’s activity and evaluating their impacts. Activity was described with an overall quantity of active travel (time or distance), a breakdown of that activity across modes (walking, running, and cycling), and—assuming the distances traveled were displacing non-active or motorized modes—the quantity of greenhouse gas emissions avoided and additional physical activity (measured in calories burned) during their active trips.

In the control condition, participants were provided with these activity metrics only, with comparisons provided between the participant’s active travel, emissions avoidance, and physical activity levels and their national average. In the test condition, several additional modules were introduced to draw on
descriptive and injunctive social norms (Cialdini, Reno, & Kallgren, 1990) and emotional cues expected to increase active travel behavior. We presented these participants with:

1. Comparisons of their activity levels and impact metrics against a “Peers” group of other participants in the study. This addition provides a descriptive norm based on others’ behavior and gives participants the ability to compare their own activity against a more meaningful, concrete, and challenging reference level.

2. Comparisons of their own emissions avoided during each week of the study, giving users the ability to easily compare their performance over time.

3. An evaluation of the participant’s performance relative to other participants, attached to an emotional cue. Participants were given one of three evaluations: “Great,” “Good,” and “Below Average.” Those who performed above their peer average were given the best evaluation; participants whose performance fell between the peer average and the national average were given a positive but challenging evaluation; and participants whose performance fell below the national average were challenged to increase their number of active trips. Following from OPOWER’s use of “smiley faces” in a set of ongoing Home Energy Report trials to “convey that energy conservation is pro-social” in the context of a household energy conservations, we also pair this evaluation with one of three emoticons to reinforce the relationships between participant behavior and these injunctive norms.

---

3 In both trials, the participant average GHG emissions were substantially higher than US and Canadian national averages, confirming that our pilot samples provided a more active baseline than a nationally representative sample.
4.3 University of British Columbia Pilot

In the first trial, we contacted a group of University of British Columbia graduate students to join a pilot study on active commuting using a mobile app for iPhones. The study ran for four weeks during April 2013, during which participants were asked to use Moves throughout the day to track their activity and send weekly reports using the app’s built-in capability to send activity records as an image. Participants
also filled out a pre-study questionnaire. Additionally, subjects in the experimental condition were asked to send daily activity summaries during the third week of the study. The purpose of this intervention was twofold: first, to create an intervention that would draw the user’s attention to their travel patterns during a particular week, and second, to determine participants’ willingness to provide reports at a higher frequency.

4.3.1 Recruitment and Sample Characteristics

We contacted approximately 140 graduate students via email with an invitation to participate in a pilot study using Moves for iPhone. Estimating that approximately 40% of those invited to join use an iPhone, our potential sample numbered approximately 55. We received 18 complete surveys, or a response rate of approximately 33% among likely eligible participants. Of these, 7 (39%) provided us with at least two weeks of user data. A description of attrition over the course of the study is presented in Table 1.

<table>
<thead>
<tr>
<th>Source of Attrition</th>
<th>Attrition Rate</th>
<th>Remaining Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>No iPhone</td>
<td>Estimate: 60%</td>
<td>55</td>
</tr>
<tr>
<td>Didn’t open email/declined to participate</td>
<td>67%</td>
<td>18</td>
</tr>
<tr>
<td>Didn’t provide data</td>
<td>61%</td>
<td>7</td>
</tr>
</tbody>
</table>

Of the 18 participants who joined the study, six were male and 12 were female. Eight participants were between 18 and 25 years old, nine were between 26 and 35, and one was between 36 and 45. In addition to basic demographic questions, we asked participants to describe their usual commutes to work or school, how often and during what seasons they bike or walk, their most important factors in choosing a commuting mode, and their political views. Asked about their most common mode for their journey to work or school, seven selected walking, one selected bicycling, eight selected public transportation, and two selected an automobile (as driver or passenger). Six participants reported cycling to work or school at
least once per month, while 12 reported cycling a few times per year or less; for pedestrians, eight reported walking to work or school at least once per month and ten reported walking a few times per year or less. The majority of cyclists (67%) reported cycling for only one season of the year, while the majority (64%) of pedestrian commuters reported walking all year around.

In terms of participant attitudes, we asked participants to choose the most important of eight factors relevant to the commute decision. Speed and convenience, reliability, and comfort were the most frequently chosen factors (12, 11, and 11 responses, respectively). Among benefits particularly applicable to active modes, health and exercise was chosen as an important factor more often than environmental impacts (ten and six responses, respectively). We also asked respondents to describe their political views on a five point scale, ranging from “Very liberal or left” to “Very conservative or right.” In addition, “I’m not political” was provided as an option. 13 respondents described themselves as “very” or “somewhat” liberal, four described themselves as centrist or apolitical, and one identified as “Somewhat conservative or right-leaning.”

4.3.2 Results
Due to the small sample size of this pilot, meaningful quantitative metrics of our behavioral intervention are not available: no consistent differences were observed in the behavior of the control and test groups. Across the group, overall activity levels were substantially (but not significantly) higher in the last week of the study (after participants were asked to provide daily activity reports) than the previous three weeks, increasing from an average of 317 minutes of activity to 528 minutes (see Figure 2). During the week in which users were asked to provide daily feedback, only three users provided data for each day of the week, suggesting that the user burden of providing daily reports is too high for it to be a viable data collection approach.
In addition to gathering user activity levels each week, participants were also asked to provide comments on positive or negative experiences using the app or the study over the course of the week. The most frequent comments (two users each) received concerned difficulty sending reports using *Moves* and problems with high rates of battery drain resulting from use of the app. One user also reported difficulty finding the app in the iOS App Store. Five users provided positive feedback regarding their experiences with the app, with three stating an intention to continue using the app after the end of the study.

This pilot study also brought two major obstacles to our attention. First, we found that users asked to provide feedback through the app’s ability to email activity summaries did not provide this information in consistent units. Because the app can display activities in units of time, distance, or steps, users did not provide us with consistent measures of their activity, requiring auxiliary assumptions about conversion factors in order to put user activity in comparable units. Combined with user difficulty in learning how to send data generally, this suggested that the app’s existing capabilities for sending data to the researcher
was inadequate. Second, we found that the process of manually creating user reports (using Excel to process data and create graphics, and InDesign to assemble graphics into a combined infographic) was quite time-consuming, requiring approximately 5 minutes of researcher time to create and send each report. While this did not pose a significant burden in this experiment, it does place a clear constraint on sample sizes: a sample of 1000 participants, for example, would require 83 hours of labor each week.

4.4 Bike to Work Week Pilot

In the second trial, we recruited participants in three Bike to Work Week (BTWW) events held in British Columbia and Minnesota to join a study on active commuting using a mobile app for iPhones. In each case, we partnered with the non-profit organization running the event in order to publicize the study. The study ran for four weeks following the BTWW events during June and July 2013, during which participants were asked to use Moves throughout the day to track their activity and send weekly reports of Moves activity metrics through an online survey form. Participants also filled out pre- and post-study questionnaires.

4.4.1 Partnership Approach

We approached four not-for-profit advocacy groups conducting BTWW events in May and June of 2013 with a description of our project and an offer to administer our study on a group of BTWW participants and share results and recommendations from each group. Three groups ultimately joined the project: Twin Cities Commuter Connection (Minneapolis, MN); HUB/Vancouver Area Cycling Coalition (Vancouver, BC); and Bike to Work BC (throughout British Columbia, excluding the Vancouver metropolitan area).
In recruiting these groups, we identified several important factors relevant to creating a successful study partnership with active transportation advocates. In addition to contacting potential partners well in advance of the study and providing detailed, accessible descriptions of the study and its potential benefits, we noted that strong follow-up efforts are required: while program managers demonstrated a great deal of enthusiasm regarding this study and quickly saw its potential benefits, the research team and program manager often needed to work together to make a case for the organization’s participation to the organization’s executive directors and boards. In particular, demonstrating complementarity with other data-gathering efforts was an important step in establishing that the study did not pose risks to the partner organization. For example, data gathering began after the conclusion of HUB’s BTWW event in order to ensure that our data-gathering process did not skew participant figures the organization had a prior commitment to provide to TransLink, the area transit authority.

Another key lesson was that, while active travel advocacy groups may have a high volume of contacts with members of the cycling community within their communities, maintaining social capital requires careful management of their messaging tools to avoid losing interest from their members and constituencies. Factors such as a perceived decrease in cyclists’ willingness to join mailing lists or register for cycling programs weigh on program managers’ decisions of how frequently to send emails, newsletters, and social media communications; this consideration places limitations on the channels through which advocacy groups can aggressively promote studies of this nature (Hill, 2013). Finally, ongoing communication during the recruitment process can help identify and resolve technical or administrative impediments to recruitment and participation.

4.4.2 Recruitment and Sample Characteristics

In our partnership with Twin Cities Commuter Connection, approximately 500 registered participants in the area BTWW were contacted via an email with a description of the study and an invitation to participate. Partners in British Columbia advertised the study to community and workplace coordinators,
who were in turn asked to invite other participants to join the study. Because of the indirectness of the latter recruiting scheme, the number of HUB and Bike to Work BC participants contacted about the study is unknown. A total of 70 participants registered for the study, with 39 joining from the Twin Cities, 17 from Vancouver, and 14 from British Columbia (outside Vancouver).

Table 3: Study 2 Attrition Sources (Twin Cities participants only)

<table>
<thead>
<tr>
<th>Source of Attrition</th>
<th>Attrition Rate</th>
<th>Remaining Participants</th>
</tr>
</thead>
<tbody>
<tr>
<td>No iPhone</td>
<td>Estimate: 60%</td>
<td>200</td>
</tr>
<tr>
<td>Didn’t open email</td>
<td>70%</td>
<td>60</td>
</tr>
<tr>
<td>Declined to participate</td>
<td>35%</td>
<td>39</td>
</tr>
<tr>
<td>Didn’t provide data</td>
<td>46%</td>
<td>21</td>
</tr>
</tbody>
</table>

Out of 70 registered participants, 35 provided activity data. A total of 102 observations were collected, or an average of 2.9 out of a possible 4 activity reports per participant. Participants were sent a prompt with a personalized link to provide activity data (in the form of time Moves recorded walking, cycling, and running) for the previous week each Sunday evening; those who had not responded within 48 hours were sent a reminder prompt. Participation generally declined over the course of the study, with 30 observations in Week 1, 26 observations in Week 2, 20 observations in Week 3, and 26 observations in the last week, for which participants were sent an additional reminder. Attrition over the course of the study was greater among participants in the control group (62%) than the experimental group (48%).

Examining the demographic structure of users who provided data, 58% of users were female and 42% were male. 43% of users were between 26 and 35 years of age and an additional 33% were between 36 and 45; with an additional 6% each in the 18-25, 46-55, 56-65, and >65 categories. A plurality of users report their most frequent commuting mode is cycling (42%), with public transportation (21%), driving
alone (15%), carpooling and walking (9% each), and other modes (3%) making up the balance of primary modes.

Asked to choose the three most important factors in choosing their commuting mode, participants cited positive health impacts most frequently (88%), followed by reducing environmental impacts (58%), affordability (48%), comfort and speed/convenience (39% each), fit with the participant’s personal image (24%), and reliability (15%). Compared to the student sample in Study 1, this group’s motives for using active modes tended much more towards discretionary, non-utilitarian considerations; in contrast to the student sample, no participants indicated that their commute choice was the only option available to them.

We also asked participants to describe their political views with regard to environmental issues through a pair of questions. The first asked participants to rate the importance of environmental protection issues “such as natural resources, biodiversity, and the climate)” in comparison to other public issues. On this question, the majority (61%) of respondents rated environmental issues as much or somewhat more important than other issues; the remainder rated them as “about as important,” while no respondents rated environmental issues as “somewhat” or “much less important.” When asked whether the burden for environmental protection ought to lie more with individual or governmental action, respondents held much more neutral opinions, with 76% indicating that the responsibility is “equal parts individual and government.” 21% indicated a greater governmental responsibility, while 3% indicated a greater individual responsibility.

Finally, we asked participants in the test group to set a goal and make a short plan for adding active trips to their routine. A slight majority (55%) indicated a goal of replacing at least one additional trip each week with cycling or walking, with another 18% willing to add one trip per month and 27% declining to set a goal (of these, a third of respondents noted that they already walk or cycle to work every day). Those who did commit to adding new trips to their routine most commonly mentioned adjusting their schedule.
(e.g. shifting work and meeting times or adjusting childcare plans), adapting to inclement weather, buying new equipment (e.g. a bicycle better suited to commuting or better outerwear), or walking and cycling for non-work errands.

4.4.3 Results

Participant activity data is inconclusive on the effects of the intervention, with no significant difference in means between the control and test group. Over the course of the trial, overall activity time increases slightly, primarily from an increase in cycling time, but the trend was not significant.

Table 4: Study 2 ANOVA Results

<table>
<thead>
<tr>
<th>Comparison</th>
<th>Means (minutes of activity)</th>
<th>F-test (p-value)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Walk</td>
<td>Bike</td>
</tr>
<tr>
<td>Experimental group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Control</td>
<td>292.7</td>
<td>279.1</td>
</tr>
<tr>
<td>Test</td>
<td>275.3</td>
<td>228.6</td>
</tr>
<tr>
<td>Week</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>279.7</td>
<td>224.8</td>
</tr>
<tr>
<td>2</td>
<td>279.9</td>
<td>237.4</td>
</tr>
<tr>
<td>3</td>
<td>280.1</td>
<td>250.1</td>
</tr>
<tr>
<td>4</td>
<td>280.3</td>
<td>262.6</td>
</tr>
<tr>
<td>Experimental group</td>
<td></td>
<td></td>
</tr>
<tr>
<td>*week</td>
<td></td>
<td></td>
</tr>
<tr>
<td>1</td>
<td>358</td>
<td>254</td>
</tr>
<tr>
<td>2</td>
<td>315</td>
<td>269</td>
</tr>
<tr>
<td>3</td>
<td>272</td>
<td>284</td>
</tr>
<tr>
<td>4</td>
<td>229</td>
<td>298</td>
</tr>
</tbody>
</table>

Responses to the post-study questionnaire provide a number of insights into the overall performance of this program. Respondents were asked to indicate if they had engaged in a number of activities since the beginning of the study. Responses are summarized in Table 4.
Table 5: Active Commuting Behaviors

<table>
<thead>
<tr>
<th>Since Bike Walk Week, have you...</th>
<th>Responses</th>
</tr>
</thead>
<tbody>
<tr>
<td>found better biking or walking routes to work, school, or other places you go?</td>
<td>7 (30%)</td>
</tr>
<tr>
<td>walked or biked with a family member, friend, or coworker?</td>
<td>7 (30%)</td>
</tr>
<tr>
<td>begun biking or walking to work or school more frequently?</td>
<td>5 (22%)</td>
</tr>
<tr>
<td>begun biking or walking to do errands, visit friends or family, or for pleasure more frequently?</td>
<td>4 (17%)</td>
</tr>
<tr>
<td>purchased equipment to improve your biking or walking commute (such as a bicycle, bicycle accessories, a bikeshare membership, walking shoes, or outerwear)?</td>
<td>2 (9%)</td>
</tr>
<tr>
<td>talked to a friend, family member, or coworker about active commuting?</td>
<td></td>
</tr>
<tr>
<td>• Yes, and I mentioned or showed them Moves or a feedback report</td>
<td>21 (91%)</td>
</tr>
<tr>
<td>• Yes, but I didn’t show them Moves or a feedback report</td>
<td>1 (4%)</td>
</tr>
<tr>
<td>• No</td>
<td>1 (4%)</td>
</tr>
</tbody>
</table>

Participants were also asked to provide responses to open-ended questions about the best and worst features of the study (including both the Moves app and the feedback reports provided). Clustering comments by commonalities, we coded 40 positive features and 20 negative features. The most positive features of the app that were mentioned included its always-on functionality (i.e. the user does not have to take any action for trips to be recorded), ease of use, and accuracy at recording trips and locations, while the most positive features of the feedback reports were the comparisons to peers provided to the test group and impact metrics of calories burned and greenhouse gas emissions avoided. Asked to note problems with the app or feedback system, frequent user complaints included app errors in mode...
identification (with misidentification of cycling trips as motorized modes and vice versa as the most common error), fast battery drain, and inaccurate recording of trip distances and times.

Asked to consider their future use of the app, 70% of users reported planning to continue using Moves after the conclusion of the study; a further 26% stated that they liked the app but encountered problems that led them to remove it, with only 4% giving an overall negative impression of the app. Additionally, 83% indicated a desire to participate in similar studies using the app in the future.

4.5 Discussion

The results of these pilots suggest several lessons for future experiments and practical implementations.

First, these results illustrate that a majority of users found value from participating in the experiment. Participants in both studies described using the app to compare their transportation behavior to that of family or friends; in the second study, where we specifically asked participants about conversations they had engaged in about active ravel, almost all users reported discussing Moves and their commuting routine with others. Large majorities also indicated a desire to continue using the app for personal purposes and to participate in similar experiments. Noting that participants were not compensated for their participation in the experiment, these responses taken together indicate a positive user experience and signal that Moves may be ready for larger-scale use in transportation data gathering.

Secondly, the large number of steps at which users may opt not to participate raise the question of whether measures are available to reduce these opportunities and increase participation. Reports of user reluctance to register for mailing lists related to active commuting programs suggest that study designs that minimize the number of emails that users will receive and do not hinge on prior registration to other programs may increase user response. Pursuing alternative means of recruiting BTWW event participants such as social media may be more effective than more conventional channels; in particular, making
recruitment materials easy for users to share with members of their social networks that may also have an interest in participation can take advantage of the high rate with which users report mentioning the app and study to others.

Improvements in the platform used for conducting these studies will also make for a better user experience and fewer opportunities for participants to cease participating. In particular, the availability of a *Moves* app for the Android mobile operating system currently in development will substantially increase the number of potential users of this system. A web-app-based automation system using the *Moves* API to automatically retrieve participant data from the *Moves* servers will also substantially reduce user burden in future studies, enhancing the quality of data available to researchers while decreasing the user burden. (For a more detailed discussion of this system, see Welsh, Baird, and Zhao (*in review*).) Future randomized studies of the *Moves* platform for behavioral interventions are planned for upcoming BTWW events in the Twin Cities area, as well as a trial among less-motivated users recruited through the online labor market Mechanical Turk.
5. WEB APP DESIGN

5.1 Introduction

Smart phones are becoming increasingly ubiquitous. In the United States, an estimated 56% of adults own a smartphone in 2013, up from just 35% in 2011 (Smith, 2013), and their increasing prevalence is transforming how corporations, governments, and other institutions interact with individuals. In the transit industry, it is increasingly common practice to provide users with trip planning services, transit schedules, notifications about service changes, and real-time arrival time estimates through mobile applications, either developed in-house (as with Toronto’s GO Transit (GO Transit, 2013) or the Missouri Department of Transportation (Missouri Department of Transportation, 2013)) or by third-party developers (as encouraged by Vancouver’s TransLink (TransLink, 2013)). Mobile apps can be expected to become an increasingly common channel through which transit providers interact with their customers.

Currently, the flow of information provided by these apps is largely unidirectional, with information going mostly from the service provider to the user. However, the potential to create a two-way information flow between service providers, researchers, and transportation planners provides an avenue for gathering rich data from users on their mobility patterns. This stream of information could allow analysts to investigate individual travel behavior over longer periods of time than feasible with existing data-gathering techniques, as well as creating feedback systems to present tailored information based on users’ past behavior.

In behavioral research in transportation conducted to date, data collection has largely been conducted through self-reports, such as travel diaries. Survey-based techniques place significant constraints on study durations and levels of detail, rely on participants’ ability to accurately describe their own activities, and can be costly in terms of time and money for transportation researchers (Schlich & Axhausen, 2003; P.
Stopher et al., 2007). Devices for objectively measuring travel, such as GPS units and accelerometers, can provide more precise metrics, but obtaining and distributing such equipment introduces substantial costs (Frank et al., 2005). Non-survey techniques such as manual and automated traffic and pedestrian counts can provide useful information about changes in travel patterns over time but lack the ability to assess the effects of user attributes such as socio-demographic profiles, values, and attitudes (Leduc, 2008). Compared to each of these methods, smartphone apps have the potential to circumvent the need for high user burdens and costly equipment purchases while gathering rich travel data from identifiable users over long study periods.

There is a breadth of mobile technologies that are of interest to transportation professionals, especially commercial apps design for fitness tracking in individuals. By utilizing with third-party applications, researchers can focus more on data analysis and less on technology development. In this chapter, we describe a web application built to facilitate data collection in a research study that analyzes feedback-mediated travel behaviors. The web app interfaces with a third-party application to automatically track participants’ travel activities, generate feedback reports based on that data, and store participant information so that it can be easily accessed by researchers. This web app is the basis of the experiments discussed in Chapter 5.

5.2 Behavioral Research

This section introduces a mobile web application developed to help facilitate a research study addressing how feedback on travel behavior can impact future travel decisions. During the study, participants tracked the amount of time they spent running, walking, or biking instead of driving or taking public transit. The study participants were provided with the Moves app so that their phone could automatically record this data for them. Each week, the participants answered a survey which asked the total amount of time they
spent walking, running, or biking during the week. The researcher then sent out personalized reports, which calculated the user’s total calories burned and carbon emissions avoided during the week. The results were averaged amongst study participants and the users were compared to their peers in the study: if they performed better than the average, they were given positive reinforcement; otherwise, they were encouraged to engage in more active travel.

This study was the motivation to develop a web application which would reduce user burden for both the researcher and the participants. The researchers save time if they do not have to create and issue a weekly survey; thus, the application should automatically collect user data from the users’ phones. Secondly, use of the application should increase participation rates: if participants do not have to spend time each week answering surveys, they might be more likely to participate in the study. With these overarching goals in mind, the web application’s primary functions are as follows:

1. Register participants for the study
2. Guide participants through the process of downloading third-party software (Moves) and authenticating the researchers’ access of the participants’ Moves data
3. Periodically gather participant data from the Moves servers, generate feedback reports based on that data, and email those reports to the participants
4. Remove users from the study if/when they wish to stop participating

All of the above functions are performed automatically by the web application. This automation is particularly significant, since these are all time-consuming activities that would have been performed by the researcher if not for the web app. Moreover, the web app is able to deal with time-sensitive tasks, such as generating and sending feedback reports in a timely manner (either immediately, or after some specified delay), which is essentially impossible to do without automation.
5.3 Design Parameters

In order to solve the problem of how to facilitate a research project that attracts as many users as possible and saves time for the researcher, there are some specific constraints that should be imposed on the web app. This section outlines those constraints and why they are necessary.

*Study Group Randomization*

In the behavioral research study, it is important to assign the users to various groups (*i.e.* control group vs. experimental groups). Thus, the web app design should perform the following functions:

- randomly assign new users to an appropriate group;
- ensure that the distribution of users into different groups is equal (or that the distribution of users in groups matches a distribution determined by the researcher);
- perform different functions for users in different groups (in the case study: send different types of feedback to users in different groups).

*Low Barriers to Entry*

The web app should not require the user to do much in order to sign up for the study. User experience gurus report that with every sign-up related task the user is expected to complete (such as filling out forms), the user sign-up rate decreases (Jarrett & Gaffney, 2009). Therefore, to maximize the amount of study participants, the web app design should accommodate these criteria:

- the sign-up procedure should involve as few clicks as possible;
- the sign-up procedure should require as little user information as possible;
- the information presented to the user during sign-up should be concise and easy to understand.
Streamlined Integration with Other Applications

Moving between the web app and auxiliary applications should be easy. Users expect a certain sophistication from mobile technologies. To retain users throughout the process, the web app should have the following characteristics:

- the app should automatically redirect users to the Moves download page (when on mobile);
- the app should automatically provide simple instructions for downloading moves (when viewed from a non-mobile device);
- any emails sent by the app should be simple, concise, and immediately actionable.

User Control over Data

It is important that users maintain control over their data. This means that the web app design should do the following:

- allow users to consent to various levels of data sharing (e.g. the user may choose whether to share location data, trip times and travel modes, or full path information);
- provide a clearly-marked, hassle-free way for the user to withdraw from the study.

Minimal User Frustrations

When the web app fails (due either to user error or to unexpected events), it should fail gracefully. With every technology, there are cases where the technology will not operate as expected, perhaps due to out-of-date software or unusual system configurations. In order to maintain good rapport with users, the web app design should follow these design guidelines:

- error messages should be clear and descriptive in layman’s terms;
- error messages should be logged and reported to the system administrator;
- when the app fails a user, the user should be provided with the opportunity to be notified when the problem is addressed.
Researcher-friendly Interface

The web app should provide the researcher with easy tools to quickly obtain data from the server. To this end, the web app should have the following features:

- an easy-to-use researcher interface for viewing meta-data (e.g. number of participants, number of records, averages);
- various options for downloading data: for instance, the research should be able to choose file format, choose level of detail, and filter by demographic.

5.4 Web App Design

5.4.1 Overview

With the above design parameters in mind, we have designed a prototype web app that serves as a “proof of concept.” This section provides an overview of what the web app does, as well as the general information flow between the app and its users (both participants and researchers). Later sections provide more detail of the data flow, and explain the web app user experience from the perspective of both a researcher and a study participant.

The system as a whole involves several key components. The agents include one or more researchers, and a (potentially large) number of participants, henceforth users. There are also two software applications: one is the web app designed to facilitate the transportation use study, and the other is the third-party application Moves. The web application is a website accessible from a mobile or desktop browser, while Moves is software downloaded directly to the user's mobile phone. Each application is associated with a different server, each of which stores data and can be accessed over the web by authenticated parties. The web app server can interact with users through the web app front end or through email; it can communicate directly with the third-party Moves server; finally, it can interact directly with the researcher
through a researcher interface or via email. Figure 3 shows all of these elements and summarizes their interactions.
Each interaction is labelled with a number and explained below.

1. Users sign up to participate in the study through the web app interface, and authorize the researchers to access their data. The web app interface provides instruction to users throughout this process.

2. The web app server stores participant data collected during sign-up.

3. Users download and use the Moves mobile application over the course of the study. Moves collects information from the user and provides the user with feedback on the user’s travel habits.

4. The Moves app transmits participant data to Moves servers.

5. The web app provides proof of authentication to the Moves server. The Moves server supplies participant data to the web app server.

6. The web app server periodically provides feedback to the user via email.

7. The web app server provides study data in a convenient format to the researcher. The researcher can access the data either directly on the server, or via a web-based platform (not pictured).
5.4.2 User Perspective

The web app performs two essential functions: the first is sign-up, in which people register to participate in the study. The second function is ongoing data collection. From the point of view of the user, some small amount of effort is required during the sign-up phase, while it is completely effortless to participate in the data-collection portion of the study.

The user’s experience during sign-up is as follows. First, the user follows a recruitment link to the web app. Ideally, this occurs on the user’s mobile device (phone or tablet) via a mobile web browser; however, the sign-up process will work equally well if the user access the web app from a desktop browser. The user might encounter the recruitment link in a variety of sources: direct email from the study facilitators, online advertisements, QR codes, social media links, communications from third-party partners (such as a Bike to Week organization), etc.

Next, the user is encouraged to enter their email address in a form on the front page of the web app. In order to make the form as user-friendly as possible, the only information collected at this point is the user’s email address. (Note that it is easy to add more form fields to the sign-up form if needed.) Alongside this small submission form are links to further information: basic information about the study, the consent information associated with the study, and contact information of the study facilitators.

After the user submits their email address, they are informed that a confirmation email has been sent to them, and they are provided with instructions to download Moves. On a mobile device, the user is provided with a direct link to the Moves page in the app store.4 On a desktop browser, the user is provided

4 “The app store” refers to either the Apple App Store (for iPhone and iPad devices), or the Android Market on Google Play (for Android-powered mobile devices). At the time of writing, Moves is only available for iOS (Apple) devices, but an Android version is in development and is expected to be released within six months. Our web app is capable of detecting whether visitors are using an iOS or Android device, and providing pertinent information accordingly.
with simple instructions for how to download and install the *Moves* app on their mobile device. The user is additionally instructed to refer to the confirmation email in order to complete the sign-up process.

Once the user installs *Moves*, the user is expected to check their email and to click the authentication link provided in the email. If the email is accessed from a mobile browser, the authentication link will take them directly to the *Moves* app, where they will be presented with an option to allow (or deny) the “Active Commuting Research App” to access the user’s *Moves* data. If the email is accessed from a desktop browser, the link will take them to a page on the *Moves* servers which will instruct the user to enter an identification number in the *Moves* app on their mobile device; entering the number will complete the authentication process.

When the user authenticates, they are automatically directed to a page informing them that their registration has been successfully completed. At this time, they are also informed of how to withdraw the researcher’s access to their data in case they wish to stop participating. (Users may withdraw from the study at any time by clicking a link in any feedback email they receive, or by directly revoking access from within the *Moves* app.) This completes the sign-up component of the user experience, which is diagrammatically summarized in Figure 2.

Once the user has signed up for the study and successfully authenticated the researchers’ access to their *Moves* data, the user does not have to do anything more in order to participate in the study, except leave *Moves* running continuously on their phone. In future applications, the researcher may wish to collect demographic or other pertinent information from study participants; in such cases, the user may also be contacted with a request to fill out a survey.

Recall the research case on which this design was based: the study requires that the users receive feedback on their travel behaviour. Under our design, the users will receive automatically-generated
infographics that summarize their recent travel activity: weekly totals for the time spent running, walking, and biking, estimations of the calories burned and CO2 emissions avoided during the week. Also reported is the national and peer averages for each of these values (peers being other participants in the active commuting study).
Figure 4: Sign-up Process Flowchart

Visual representation of the sign-up process from the perspective of the user. Blocks represent “pages” that a user can view; arrows indicate user actions. Note that “failure states” (error pages) are not represented on this chart, even though they are present in the app prototype. (For instance, if the user does not submit a valid email address in the sign-up form, they are requested to re-submit the form.)
5.4.3 Data Flow

This section details the web application’s two primary procedures: sign-up (occurs once per participant) and periodic data collection (which occurs repeatedly over the course of the study). Each procedure is facilitated by the web app server.

5.4.3.1 Sign-up

During sign-up, the following process takes place (illustrated in Figure 3):

1. The user enters their email address on the sign-up page. This action activates a “sign-up script” on the web server, which generated a new database entry for the user and sends an email to the specified email address.

2. Upon entering their email address, the user is redirected to a page which instructs them to download third-party software *Moves*, and provides a link directly to the app store to facilitate this process. The user is also instructed to check their email after *Moves* has been downloaded.

3. The email that is sent to the user includes a unique authentication link. Clicking this link will start the authentication process, in which the user authorizes our web app to access their data collected by *Moves*.

4. When the user authenticates through *Moves*, the web app server communicates directly with Moves to retrieve “access credentials,” which allows our web app to download that user’s data on the *Moves* server. These credentials are valid until the user explicitly revokes them.
Figure 5: Sign-up Data Flow

Data flow during the sign-up phase. The process flows from top to bottom. Arrows indicate actions by either the user or a server. The user initializes the process by entering an email address at the web app front page; this activates a chain of events detailed in the text.
5.4.3.2 Ongoing Data Collection

After sign-up occurs, the web app server can access user data on the Moves server indefinitely (until access is revoked by the user). Until this occurs (or the study ends), the data flow is as follows (illustrated by Figure 4):

1. The participant uses Moves in day-to-day activities. Moves runs continuously on the user’s phone, automatically detecting the user’s travel behaviour and recording this information in the form of a “storyline.” The data consists of travel times, mode of travel, and start and end locations for each trip.

2. Periodically, Moves servers download user data from the user’s mobile application.

3. Every week, the web app servers pull new data from the Moves servers for all users currently participating in the study. (It is also possible to change the data collection period from one week to any other length of time.)

4. The web app server automatically generates information feedback infographics for each user in the study. These infographics are emailed to the study participants as part of the study design.

5. The researcher can then access the study data at leisure, either by directly accessing the database on the web server (not pictured in Fig. 4), or by using the web app researcher interface.
5.4.4 Researcher Perspective

The transportation professional’s interaction with the web application begins when the researcher downloads user data. Participant data is stored on the web app server within MySQL database tables.
These database tables can be accessed directly on the server, or via the simplified “researcher interface” built into the web app.

If the researcher is trained in the use of database queries (specifically SQL syntax), they can log on to the web app server directly to download participant data. This option is quite powerful, as sophisticated database queries can quickly and easily pull out data filtered according to whatever the researcher needs. In the current implementation, the researcher can filter based on the date the data was recorded, particular classes of data (e.g. walking trips, cycling, or driving), and more. The researcher can also connect to the database through third-party database management software or, if desired, via a command-line environment.

For the researcher that doesn’t have the background in database query syntax, there is a simplified option for downloading user data. At present the web app presents a simple form to the researcher, allowing them to download user data in a CSV format within a specified range of dates. This capability could be expanded in future development of the software in order to allow for more complicated queries and to provide more export options.

While the web application currently only collects travel data in conjunction with Moves, the researcher might require additional data, such as demographic data. In the current system, the researcher would download the e-mail address of active participants from the web server, create a demographic survey through a third-party survey administration system, and contact the participants directly to solicit the desired data. In future development, this functionality could be integrated into the web application, so that researchers can conduct surveys directly from the web application.
5.4.5 Implementation

The web application was developed on the Django web framework, which is written in the Python programming language. Django, like Python in general, is a widely used web framework with a breadth of useful libraries that vastly increase the speed of development, allowing sophisticated web applications to be built swiftly. The popular database management system MySQL underlies the application. The web application prototype is hosted on servers at the Massachusetts Institute of Technology.

5.5 Discussion

Our web application is the interface between a generic tracking app, *Moves*, and transportation research (including data collection or surveys, information feedback, and experiment implementation). While it was designed with a particular experiment in mind (behavioral nudging) and a particular third-party software, *Moves*, in theory our platform can connect with any *Moves*-like application that provides an API (*i.e.* an application programming interface: used to “share” data between different applications).

5.5.1 Desired Features

While essential features have been implemented into the prototype, there are several features that could be developed on top of the existing application that would make the application even more useful to both researchers and the end user. Such features include a “user portal” for users to view their statistics online via the web app, and an expanded researcher portal.

In the behavioural nudging study, users were provided with weekly summaries of their travel behaviour. In these reports they received information about the total time they spent that week in various modes of travel, estimations of the amount of carbon emissions avoided by active travel methods, estimated calories burned in active travel methods, and a comparison of the user’s performance with their peers in the study and the national average (of Canada or the USA, depending on the user’s location). These values were reported to each user via a personalized infographic, which was distributed over email. It would be useful
to have the web app double as a portal for users to login, check their weekly stats, visualize their travel history and/or environmental impact, compare performance with others, and possibly even integrate this experience with various social media outlets.

Another useful feature would be an expanded researcher portal. At present the researcher can use the web app to download all user data within two specified dates; more sophisticated database queries can be made directly to the database. One useful feature would be a robust database search tool built in directly to the web app. It would also be useful to have a user-friendly way for the researcher to visualize participant groups.

One researcher-focused tool that would be particularly useful is a built-in survey administrator tool. The web app currently collects Moves data and an email address; with a survey tool, the app could also collect demographics and other survey data. With further development, such a tool could certainly be implemented within the current application framework.

5.5.2 Future Applications

While the web application has been developed with a particular research goal in mind (as a means to implement Behavioral Nudge experiments), there are many other problems that can be addressed with a similar platform. As a data collection tool, the system could supplement or even replace the traditional household travel diary survey. If combined with a transit smartcard, such as the Oyster in London or the Compass card in Vancouver, the resulting travel data could be incredibly rich. Finally, by combining Moves, our web app, an Oyster/Compass-type pass, and a questionnaire survey, researchers can get a picture of multi-modal travel with complete spatial and modal coverage and longitudinal tracking at no marginal cost. There are a wide variety of other functions that the web app could serve. In the case of transit network design and optimization, researchers could collect data on exact trip durations and routes (including ‘last mile’ legs of the trip made on foot or by bicycle), wait times, and correlations between
home and work location and the use of transit. It could also provide detailed and powerful information on usage of different bicycle routes throughout a city to guide investment in improved cycling infrastructure.

5.6 Conclusion

The commercially-available mobile app *Moves* is a sophisticated tool for collecting user travel data, automatically detecting travel methods during trips, and potentially doing much more. In order for it to become a powerful tool for transportation researchers, there must be a way of gracefully collecting user data from the application. This demands an automated procedure for obtaining authenticated access to user data, as well as regularly retrieving and storing user data. Our web app is a proof-of-concept that this is possible; in this paper we have presented a prototype of an agile web application that provides an interface between users and the third-party application *Moves*. The web application is designed to reduce the complexity of the experimental design process for the researcher while simultaneously improving the user experience. This paper has explored some of the promising aspects of the approach.

While other mobile applications aim to replicate the functionality of apps like *Moves*, specifically in travel research settings, these all require full attention from study participants. Our web application combined with *Moves* requires almost no user interaction. *Moves* runs continuously in the background of the user’s phone. The web application’s data collection requires no user interaction beyond the initial sign-up.

Mobile technology has tremendous potential to facilitate transportation research, but there are challenges to be aware of when using these tools. Data privacy and security are important to keep in mind. The design of tools for enhancing travel research should also address concerns of user-friendliness, accessibility, clear communication, smooth interfacing with third party software, scalability, and keeping software up to date.
With the increasing prevalence of smartphones, the automated collection of travel data—including routes, mode of travel, and timing—is becoming a service rather than a unique tool. The role of the researcher is shifting from data producer to data consumer; with clever use of sophisticated consumer travel apps readily available on the market, transportation researchers can spend less time thinking about data collection and more time formulating new hypotheses to test with existing data. Using data in this fashion expands the universe of travellers that researchers can reach. Widespread use of such a system holds promise for beginning to universalize the conclusions drawn from analysis of individual cities, and can allow for continuous replication testing.
6. FURTHER EXPERIMENTAL DESIGNS

6.1 Introduction

In the experiments presented in the previous chapter, we recruited two small groups of users with the primary goal of gathering preliminary results and understanding the data, technology, and communication needs of a large-scale experiment. Our results have indicated a high degree of user satisfaction with the Moves app and feedback system, with many participants expressing interest in continuing to participate in related research. Applying the lessons learned from these trials, as well as an improved data-gathering and feedback platform that leverages the Moves API to automatically retrieve and process user data and send feedback reports, substantially lowering both user and researcher burden. (More details on the implementation of this system are presented in Chapter 6.)

The two experimental designs presented in this chapter are as follows:

3. **Mechanical Turk Experiment**: upon completion of a data-gathering web app using the Moves API, we plan to test a design that better measures the effects of our behavioral feedback reports with members of the Mechanical Turk online labor marketplace. Control participants will receive no feedback reports, while test participants will receive additional comparisons, an emotional cue, and a prompt to set active commuting goals. 250 participants will be recruited and asked to install Moves and authenticate with a web app that will allow the research team to gather one month of travel records and send feedback reports with minimal participant effort.

4. **Twin Cities Commuter Connection/Metro Transit Experiment**: upon completion of a data-gathering web app using the Moves API, we plan to partner with Twin Cities Commuter Connection to implement Moves as a primary data gathering instrument for a September 2013 Bike to Work Week. Increased promotional efforts, automated data collection, and the availability of an Android version of the Moves app is anticipated to provide a larger sample.
Table 6: Comparison of Experiments

<table>
<thead>
<tr>
<th>Experiment</th>
<th>Methods</th>
<th>Interventions</th>
<th>Population</th>
<th>Sample</th>
</tr>
</thead>
<tbody>
<tr>
<td>1. UBC Pilot</td>
<td>Manual entry and report creation</td>
<td>Weekly basic vs. weekly enhanced feedback</td>
<td>Students, moderately motivated</td>
<td>Recruited: 17 N = 7 Duration: 4 weeks</td>
</tr>
<tr>
<td>2. BtWW Pilots</td>
<td>Survey-based entry and automated report creation</td>
<td>Weekly basic vs. weekly enhanced feedback with goal prompt</td>
<td>Bike to Work Week participants, highly motivated</td>
<td>Recruited: 70 N = 35 Duration: 4 weeks</td>
</tr>
<tr>
<td>3. MTurk Experiment</td>
<td>Fully automated entry and report creation</td>
<td>No feedback vs. weekly enhanced feedback and goal prompt</td>
<td>MTurk users, self-selected but not necessarily highly motivated</td>
<td>Target N = 250 Duration: 4 weeks</td>
</tr>
<tr>
<td>4. TC Experiment</td>
<td>Fully automated entry and report creation</td>
<td>Monthly feedback vs. weekly enhanced feedback and goal prompt</td>
<td>Bike to Work Week and rideshare program participants</td>
<td>Target N &gt;= 100 Duration: ongoing</td>
</tr>
</tbody>
</table>

6.2 Mechanical Turk Study

In order to provide a stronger test of our feedback system, we will conduct an experiment among participants recruited from Mechanical Turk, an online labor marketplace operated by Amazon.com. Participants will be divided into a control group and an experimental group. The experimental group will receive detailed feedback in the same configuration as participants in the past experimental groups, while the control group will receive no feedback during the duration of the experiment. For the user’s

2.1 Recruitment Using Amazon Mechanical Turk

Data collection and survey distribution will be performed using the Amazon Mechanical Turk (AMT) online labor marketplace. MTurk is a popular crowdsourcing system that provides employers and researchers with access to a large and diverse pool of online workers (Turkers) who perform short tasks for a reward or wage. As of 2012, AMT reported a workforce of 500,000; demographic studies have found that approximately 57% of workers are located in the United States, 32% in India, 3% in Canada.
Studies have shown that AMT participants are significantly more demographically diverse than university samples—characterized as “western, industrialized, educated, rich, young and democratic” (Henrich, Heine, & Norenzayan, 2010)—and relatively representative of the US population of internet users. The representativeness, reliability, and quality of data collected was also found to be at least on the same level as traditional surveying methods (Buhrmester, Kwang, & Gosling, 2011; Paolacci, Chandler, & Ipeirotis, 2010). Initial agreement on the validity of AMT as a tool for research has been reached within the fields of political science and judgement and decision making (Berinsky, Huber, & Lenz, 2011; Paolacci et al., 2010). A number of influential findings from the cognitive behavioral psychology literature have also been replicated with populations of Turkers, including tests of attention, priming, and learning tasks (Crump, McDonnell, & Gureckis, 2013). AMT’s crowdsourcing mechanism contains an inherent self-selection process, as workers have a wide range of tasks they may be qualified to work on and must choose which to complete. AMT’s overall North American subject pool appears to have greater representativeness of North American commuters than many other options, such as university-based sample.

To recruit AMT participants, we will post an assignment to the Mechanical Turk board. Access will be restricted to users located in the United States, who are 18 years of age or older, who own a Moves-compatible smartphone, and who have commuted to work or school by bicycle or walking at least once in the past four months. Participants will be asked to commit to installing the app, using it for the following four weeks, and answering a follow-up survey at the end of the study period. Those who successfully complete the first survey and install the app will be paid $0.50 USD; after completing the data collection phase of the study, they will be paid an additional $2.00 USD. Users who opt out of the study after completing the initial survey but before the conclusion of the data gathering period, or who do not use
Moves for a sufficient duration to establish a reliable travel record, will be paid an amount proportional to the number of weeks they participated and provided adequate data.

6.2.2 Experimental Design and Interventions

250 participants will be recruited, with 125 assigned to each experimental condition. Those in the control group will be asked to complete the short survey (below), install and authenticate the Moves app, and carry their phone with Moves enabled for at least eight hours per workday for the next four consecutive weeks. Users in the experimental group will be invited to set an active travel goal and will also receive weekly feedback reports similar to those used in the previous Bike to Work Week pilot and be asked to take 2-3 minutes each week to review these reports. After receiving four weeks of feedback, users will be asked to complete a post-study questionnaire (below).

6.2.3 Data

Respondents will be asked to provide behavioral and demographic information through a brief survey, as well as installing the Moves app and verifying it with our web app.

6.2.3.1 Survey

Users will be asked to complete a short questionnaire asking for the following information:

1. **Filtering Questions:** participants will be asked if they have biked or walked to work or school at least once in the previous four months. They will also be asked if they own and use a compatible iOS or Android device on which they can install the Moves app; if the answer to either of these questions is no, the participant will be thanked and directed out of the study. Finally, a filter question that asks the participant for a specific answer (e.g. “Respond to this question with the number ‘3’”) will be included as a criterion to exclude survey answers that may be unreliable.
2. *Active Travel Behavior*: participants will be asked how often they bike or walk to work or school, for errands, and for other trips.

3. *Mode Choice Motivations*: participants will be asked to choose their three top motivations for their mode choices out of a set of utilitarian, social, and values-based motives.

4. *Environmental Values*: participants will be asked a pair of questions to determine the degree to which they prioritize environmental protection over other pressing public issues, and whether they view environmental protection as primarily a government or individual responsibility. These questions are designed to measure the extent to which political and environmental values may be salient motivators for these users.

5. *Demographic Characteristics*: participants will be asked to provide their age, gender, and household income.

Additionally, participants assigned to the experimental group will be invited to set a goal to walk or cycle more often, and prompted to describe a plan for doing so. However, participants can opt not to set a goal without consequence.

After the data-collection period has been completed, users will also be asked to complete a follow-up questionnaire asking for the following information:

1. *Active Travel Behavior*: participants will be asked how often they bike or walk to work or school, for errands, and for other trips. This will serve as a method of comparing self-reported activity behavior with objectively measured trip data from *Moves*. They will also be asked if they have taken specific actions, such as walking or biking with a friend, family member, or coworker, or purchasing equipment for active travel (such as outerwear or bicycle accessories).
2. **Mode Choice Motivations**: participants will be asked the same questions about motivations for their mode choices as in the pre-study questionnaire. This will allow us to measure the effect to behavioral interventions on motivations conducive to active transportation.

3. **User Satisfaction**: participants will be asked whether they intend to continue using the *Moves* app (and if not, whether it is out of disinterest or problems with the app), as well as whether they have discussed the app or feedback with others.

After completing this final survey, users will be paid for their time and participation over the course of the study.

6.2.3.2 *Moves and Web App*

Participants will be asked to install the *Moves* app on a compatible iOS or Android device, authenticate it with the web app developed to gathering data through the *Moves* API system, and carry their phone with *Moves* enabled on a daily basis for at least 8 hours during the workweek. Participants will be advised that the app may cause greater than usual battery drain on their phone, and suggest that charging during the day may be helpful or necessary to gather data throughout the day. Using the web app, the research team will be able to download user data on trips (including modes, durations, and distances) as well as a daily record of locations over time.

Data from *Moves* will be collected via the web app for the four full weeks following registration. Participants in the experimental group will be provided with feedback reports following each week of data collection. At the beginning of the study, participants will be provided with instructions on how to opt out of the study by contacting the research team; after the conclusion of the study, participants will be instructed that they can cease participating either by uninstalling the app or contacting the research team to cease data collection. Depending on the number and characteristics of users who continue using the app
and do not opt out, the research team may continue collecting data on this sample of users for up to two years. Users who do not opt out in the experimental group will continue to receive feedback reports, with a link included in each report to end participation in the study. Users in the control group will receive periodic thank-you messages for their continued participation, with a similar link to end their participation.

6.3 Fall 2013 Bike Walk Week Study

Our success in bringing enthusiastic partners from the active travel advocacy community is an important asset from prior studies, and we plan to continue to build on these relationships to recruit participants in Bike to Work Week events. The next planned trial will take advantage of our data-gathering web-app to conduct a larger-scale trial among commuters in the Twin Cities, Minnesota metro area, using a snowball sampling technique to take advantage of user enthusiasm for the app as well as increased publicity on social media.

6.3.1 Recruitment Using Social Media

Based on the recruitment patterns observed in the first study, two major factors have influenced our recruiting approach. First, discussions with Jessica Hill, program administrator at partner organization Twin Cities Commuter Connection, revealed that only 500 of the event’s 12,000 to 15,000 participants registered for the event’s mailing list. While levels of participation vary widely, from leadership and daily participation to biking or walking for just one trip, we noted that other means of recruitment may significantly enhance awareness and participation in this study. Second, responses to our post-survey of BTWW participants indicated that a large majority of participants had discussed the Moves app and/or our study with a friend, family member, or coworker and were interested in continued participation with
similar studies, indicating a high potential for additional recruitment through a chain referral or “snowball sampling” approach aided by social media (Biernacki & Waldorf, 1981).

To reach new users directly, we intend to distribute invitations to participate through existing email mailing lists as well as social media (Facebook, Twitter, Google+, and Reddit) channels and handouts and posters for events and workplaces with QR codes to expedite registration. The study will be publicized on social media channels on a scheduled basis, with messages marked with searchable hashtags that interested users may be following, such as “#bikewalkweek” or “#biketc.” Dedicated social media accounts may be used to contribute to discussions related to active travel and further publicize the study as relevant opportunities appear.

We also intend to facilitate snowball sampling by providing users with easy methods of inviting members of their social networks to join the study, including email invitations and links to post on social media. Users who noted a desire to participate in future studies present an especially strong opportunity to spread our platform: by inviting these ‘SuperMovers’ to join our new data-gathering platform in advance of the Bike Walk Week, we can eliminate any errors in the system, as well as encouraging them to publicize the study among friends and coworkers. By tracking referrals, we will also have the opportunity to learn about the behavior of cyclists and pedestrians with greater social influence on others.

The use of social media services as a platform for snowball sampling is relatively new. Its use has been pioneered in the fields of medicine, nursing, and public health, where social media has allowed recruitment of individuals with rare health conditions or assessing prevalence of health conditions or behaviors among a highly specific population (Sadler, Lee, Lim, & Fullerton, 2010). This approach has very recently been attempted in social research for less specialized populations with the goal of increasing the efficiency of recruitment for studies of defined populations, with considerable success in attracting large samples with considerably less time and effort than required in many other recruitment strategies.
(Brickman Bhutta, 2012). In this experiment, the social structure by which the Bike Walk Week is publicized (e.g. through social media and workplace networks) parallels the recruitment strategy used. While this approach is unlikely to produce a representative sample of all commuters who a transportation agency, municipality, or active transportation advocate might wish to target, it can be expected to produce a similar group of participants as those who might take part in other active travel promotions.

6.3.2 Experimental Design

Participants in the control condition will be asked to install and authenticate the *Moves* app, complete the survey sent after registration, and carry their phone with *Moves* enabled during each weekday, and will receive limited monthly feedback reports on their travel behavior. Users in the experimental group will be invited to set an active travel goal and receive weekly feedback reports similar to those used in the previous Bike to Work Week pilot. After receiving four weeks of feedback, users will be asked to complete a post-study questionnaire (below), but users will be invited to continue participating and receiving monthly (control) or weekly (experimental) feedback reports.

6.3.3 Data

Participants will be asked to provide responses to a brief questionnaire, as well as installing the *Moves* app and verifying it with our web app. In order to maximize participation and limit sources of attrition, we avoid requiring users to provide questionnaire responses during the recruitment process, employing a follow-up survey after registration instead. During the initial recruitment step, users will be asked to provide only an email address for future contacts; once this information has been gathered, participants will be redirected to install the *Moves* app and verify it with our web app. Once this step has been accomplished, the research team can begin collecting user data.

6.3.3.1 Survey

Approximately one day after registering for the study, participants will be asked to complete a short questionnaire asking for the following information:
1. **Active Travel Behavior**: participants will first be asked how often they bike or walk to work or school, for errands, and for other trips.

2. **Mode Choice Motivations**: participants will be asked to choose their three top motivations for their mode choices out of a set of utilitarian, social, and values-based motives.

3. **Environmental Values**: participants will be asked a pair of questions to determine the degree to which they prioritize environmental protection over other pressing public issues, and whether they view environmental protection as primarily a government or individual responsibility. These questions are designed to measure the extent to which political and environmental values may be salient motivators for these users.

4. **Demographic Characteristics**: participants will be asked to provide their age and gender.

Additionally, participants assigned to the experimental group will be invited to set a goal to walk or cycle more often, and prompted to describe a plan for doing so. However, participants can opt not to set a goal without consequence. After the data-collection period has been completed, users will also be asked to complete a follow-up questionnaire asking for the following information:

1. **Active Travel Behavior**: participants will be asked how often they bike or walk to work or school, for errands, and for other trips. This will serve as a method of comparing self-reported activity behavior with objectively measured trip data from *Moves*. They will also be asked if they have taken specific actions, such as walking or biking with a friend, family member, or coworker, or purchasing equipment for active travel (such as outerwear or bicycle accessories).
2. *Mode Choice Motivations*: participants will be asked the same questions about motivations for their mode choices as in the pre-study questionnaire. This will allow us to measure the effect to behavioral interventions on motivations conducive to active transportation.

3. *User Satisfaction*: participants will be asked whether they intend to continue using the *Moves* app (and if not, whether it is out of disinterest or problems with the app), as well as whether they have discussed the app or feedback with others.

### 6.3.3.2 Moves and Web App

Participants will be asked to install the *Moves* app on a compatible iOS or Android device, authenticate it with the web app developed to gathering data through the *Moves* API system, and carry it on a daily basis during the workweek.

Recruitment will begin three weeks prior to the Bike Walk Week event, creating time for *Moves* users to try and share the app, as well as allowing time for the research team to gather one to three weeks of pre-intervention data on participants. Beginning in the week of the Bike Walk Week, participants will begin receiving feedback reports, and will continue receiving them for the following three weeks. After three weeks of post-intervention data have been collected, users will be contacted to complete the follow-up questionnaire describe above. Users will have the option of opting out of the study at this point, but will be invited to continue using the *Moves* app and receiving feedback reports.

### 6.4 Research Goals and Discussion

Both of these experiments apply the experimental approach developed in our previous pilot studies to larger-scale experiments that can provide the sample sizes necessary to better test the efficacy of feedback reports as a travel behavior modification strategy. In the first experiment, AMT provides a means of gathering a sample of a defined size quickly and at low cost while providing potentially greater
demographic and motivational diversity than other convenience samples such as university students. In addition, the fact that users are paid to participate for a defined period of time allows us to study the effects of behavioral feedback reports as a whole, rather than the effects of variations between different types of report content.

In the second experiment, continuing to build on prior collaboration with active travel advocates allows us to learn from experiences in earlier trials to more effectively recruit and retain participants, providing them with a valuable and enjoyable source of information about their active travel while gathering an even richer set of data than previously available. The data produced here can inform a more detailed understanding of how active transportation behaviors vary among users with different levels of commitment, as well as providing insight into how interventions operate on users with greater or lesser levels of pre-existing commitment to walking or cycling. In addition to providing a test of the effectiveness of our behavioral interventions, this trial will also serve as a demonstration of the feasibility of a highly automated app-based travel data gathering platform, either for measuring the effectiveness of specific, short-term interventions (e.g. as a preferred approach to recording personal or team active trips for workplace or school-based active commuting competitions), or monitoring the behavior of groups of users over long periods of time. In particular, the willingness of participants to continue using Moves, authorizing data collection through the web app, and viewing feedback reports can be tracked.
7. CONCLUSION

7.1 Key Findings

The central findings of this thesis are as follows:

7.1.1 The Potential of Behavioral Economics to Enhance Transportation Models and Interventions

Reviewing the literature from behavioral economics on various facets of consumer decision-making, such as the use of heuristics and mental accounting schemes and the influence of norms on decisions with social ramifications, we identify several areas in which transportation researchers and practitioners can improve their ability to understand, predict, and influence travel choices, such as when and how users are charged for their travel activities and how information on the impacts, typicality, and availability of different travel options are presented.

7.1.2 Approaches to Behavioral Design of Travel Information

Behavioral interventions are a promising, if unproven, avenue for increasing active travel and decreasing motorized trips. However, testing and implementing this approach requires considering a broad range of possible techniques of presenting information to users. To facilitate future designs under this paradigm, I review a number of parameters that must be considered in a feedback report or similar behavioral tool using the data available from activity tracking apps such as Moves. Referring to this list provides a framework for designing and delivering information products to users, as well as suggesting useful variants to be tested using RCT approaches, particularly where large, long-term user groups are available.

7.1.3 Lessons for Research Partnerships with Active Travel Advocates

The effectiveness of the behavioral interventions we propose may be seen most readily among populations for whom cycling and walking are viable modes of transportation to work, school, or other destinations—that is, those whose primary barrier to greater levels of active cycling is based on motivation, rather than the constraints of the built environment.
Rather than attempting to find and recruit people who fit this profile from scratch, organizations such as active travel advocates have ready access to populations that have already expressed interest and enthusiasm for walking and cycling. Program managers for these organizations tend to share this enthusiasm for tools that can cheaply expand their ability to communicate with and motivate their constituencies. However, the process of developing relationships and finding paths towards mutually beneficial research strategies is vital to making these partnerships a reality. Researchers interested in the characteristics and behavior of dedicated cyclists and pedestrians may find considerable value in partnering with these organizations, but should keep in mind the resource constraints, prior data-gathering commitments, and need for caution with social capital that these organizations face. The best collaborations with active travel advocates can yield new insights for both research and practice, creating useful knowledge for both parties.

7.1.4 Viability of Commercial Activity Tracking Apps for Travel Data Collection

The pilot studies described in Chapter 4 provide a clear demonstration that, even with a less-than-ideal technical approach to data-gathering and report generation, a commercial activity tracking app can be used to gather detailed, objectively measured data from volunteer participants, as well as providing feedback reports with meaningful metrics and comparisons of behavior over time. The overwhelmingly positive responses to questions intended to assess satisfaction with the platform used in this study provide a strong indication that Moves and similar activity tracking applications are a viable platform for further experimentation. Enhancements to both the Moves platform (such as ongoing accuracy and battery efficiency improvements, and an Android version of the app) and scripts developed to interact with the Moves API and send feedback reports will all enhance the user experience with this system, further increasing our ability to gather data for long periods of time across users with different levels of engagement.
7.2 Limitations

A number of limitations exist to the framework and empirical tests described in this thesis, including concerns relating to privacy and the handling of sensitive data, equity issues relating to the use of costly smartphone technology as a basis for research and data-gathering, objections to the ‘nudging’ framework that underlies the behavioral intervention approach I advocate, and limitations on the inferences that can be drawn from the highly self-selected populations studied in Chapter 4.

Ongoing societal conversations about data privacy have become more pressing in recent years as the volume of data collected, stored, and analyzed by governments, corporations, and NGOs has increased tremendously. Core questions include the ownership of data collected as a result of user interactions with web-based services (such as search engines or social media) and how researchers can responsibly use data collected in the course of user interactions with services that are provided primarily for non-research uses.

In the studies described in this thesis, users were clearly notified of their rights as participants in a human subjects experiment governed by university ethics review. However, as activity tracking apps become more common as a measurement tool for researchers outside of university settings, including advocacy groups and employers, the distinction between the app as a tool for the end-user and as a data-gathering instrument for the research may become blurred. Further attention will be needed to ensure that participants retain control over who has access to location and activity data generated by apps such as Moves, the purposes they can be used for, and what sorts of feedback and messaging they may be exposed to. It is in the interests of researchers to be attentive to how treatment of these questions can enhance or damage user trust, as well as how clear, well-designed default options can help users select an appropriate level of disclosure and participation.
Another limitation of my data-gathering framework is inherent to the use of mobile technology: not all users who might benefit from activity tracking apps have access to smartphones and the necessary data plans to use these apps. Conversely, unequal representation of different socio-economic or geographical groups in user samples may limit the applicability of experimental findings on behavioral interventions. While the potential for behavioral interventions tested under this paradigm to be less effective in groups with lower-than-average access to smartphones and ability to find and install apps like *Moves* is unlikely to cause direct harm to vulnerable populations, a more serious concern is that increasingly app-driven data gathering approaches may begin guiding investments in costly programs and infrastructure. While this approach could provide excellent, high-quality data for a variety of planning and project evaluation purposes, it also might begin inadvertently excluding the travel patterns of vulnerable populations, including people with disabilities or low incomes, and both children and the elderly.

As app-based data gathering approaches become more prevalent, practitioners must consider what groups may be excluded under this approach and formulate strategies for either supplementing mobile trip data or extending access to mobile connectivity among these groups. However, some groups and individuals may remain inaccessible to this data-gathering approach: in addition to the vulnerable populations mentioned above, this approach may also exclude individuals who place a high value on personal privacy and avoid sharing information about their location and routine with outside parties.

Another limitation on the applicability of the approach described in this thesis is the potential for objections to be raised to the concept of behavioral interventions or ‘nudging’. Since the introduction of this concept by Thaler and Sunstein, this approach has drawn both positive and negative attention from authors concerned with the ethics of medical practice, marketing, and public policy. Objections to nudging include claims that the approach reduces peoples’ capacity to exercise good judgment independent of someone else steering our choices; that an expert-driven approach to managing behavior
might diminish the value of individual participation in the public sphere; and that those who act as choice architects may mistake unfamiliar values or preferences among a given population for biased decision-making, leading to nudges that do not actually increase well-being as experienced by the population in question (Selinger & Whyte, 2011). While examining the validity of these objections and when they might constitute compelling reasons not to change behavior in this way is beyond the scope of this thesis, these are important questions for planners and public officials to consider before applying this approach outside of self-selected groups.

Finally, the behavior and user experiences recorded among Bike to Work Week participants in Chapter 4 should be interpreted in the context of sample that is not necessarily representative of current or potential active commuters in general. The highly positive user experiences of participants speaks to the viability of Moves as a platform for data gathering and behavioral interventions, but as a highly motivated group, the level of enthusiasm and willingness to participate in a somewhat burdensome study without payment is likely to decline among more broadly representative groups of users. Attention to creating a positive user experience and minimizing effort in future studies should remain a priority, especially as activity tracking apps are used among more heterogeneous populations. The sample may also be unrepresentative to the extent that they have successfully integrated cycling into their lifestyles to the maximum extent feasible. However, the data collected on most frequent modes and the number of participants willing to set goals for adding additional active commutes to their routines suggest that, among many participants, this point has not yet been reached.

7.3 Implications

Within the discipline of city planning, practitioners and theorists identify with a broad set of skills and activities that make up the professional identity of planning. Planners act as designers and visualizers;
cartographers and videographers; negotiators and facilitators; analysts and researchers; and managers
people, budgets, projects, and expectations. Different practitioners identify with these roles in varying
proportions: some find a specialized role to fit their talent, while others embrace a generalist practice.

However, whether a planner operates broadly or narrowly, none of these roles capture the core of what
planners do. In fact, many of the signature skills and abilities of the planner are embodied more fully by
members of other professions, whether in the design skills of architects and landscape architects, the
sophisticated modeling techniques of engineers and economists, or the messaging and political savvy of
full-time advocates, marketers, and politicians. However, planners do play a distinct role in their
institutional environments is by providing a distinct future orientation and interdisciplinarity. By bringing
different perspectives and interests together to think about opportunities and problems that may happen
decades from the present, they hope create more robust and resilient policies and cities.

While this is an undeniably important part of the profession’s identity, I suggest that this is not the only
special role of the planner, and their future-oriented role is in fact being shared with an increasingly broad
group of other professions. Journalists, technologists, politicians, and academics of all stripes frequently
lay claim to the same territory of generating visions of the future city and of the urban life of tomorrow,
sometimes into far more distant futures than planners care to contemplate. The increasing prominence of
urban issues in contemporary popular media (such as The Atlantic Cities, a publication that exclusively
covers issues of planning, design, and urban economies) has made this tendency more visible to the public
in recent years. Additionally, many of the most influential figures in defining the goals and methods of
planning have in fact come from outside the profession. Activists and social critics like Jane Jacobs and
James Howard Kunstler, architects from Le Corbusier to Andres Duany, and non-planner academics
including Lewis Mumford, William H. Whyte, and David Harvey all stand among the most important
influences on the field today (Planetizen, 2009). Finally, the emergence of tactical urbanism’s model of
agile and experimental interventions has inspired planners to adopt a more near-term orientation (Lydon, Bartman, Woudstra, & Khawarzad, 2010).

All of this suggests that the planner’s role as an urban professional cannot be neatly described by their skills, subject matter, or time-orientation. A possible way to conceptualize the sort of planning interventions discussed in this thesis and elsewhere is to view the planner as a choice architect.

In their 2008 book *Nudge*, Richard Thaler and Cass Sunstein describe a hypothetical manager of a public school system’s cafeterias who learns that students walking through the lunch line tend to take more of whatever foods are at eye level. If the cafeteria workers put cookies and pizza in that space, the students will eat more cookies and pizza. If they replace the cookies and pizza with salad and whole grains, students eat more of those foods instead. Crucially, nothing about the options in front of the students has changed—cookies, pizza, salad, and whole grains all remain on the menu, and their prices do not change. To an economist, the incentives the students faced in each case were exactly the same—yet the manager discovers that the amount of each food consumed will differ substantially as a result of this seemingly minor detail (R. Thaler & Sunstein, 2008).

Faced with this information, the manager has a decision to make: should she leave the items the way they were, or perhaps place them randomly to make the children’s choices ‘fair”? Or should she use this information to help the students choose healthier foods? Thaler and Sunstein call the manager a choice architect: she has the opportunity to frame the decision that her students make in order to promote a particular set of goals, *without restricting their freedom to ultimately make their own choice*.

Like the cafeteria manager, planners often find themselves with the job of presenting options to groups of colleagues, the public, or the politicians and officials with the authority to choose what policies to implement. More often than not, planning research is conducted to inform a choice that is not wholly the
planner’s role, then, is not simply to provide accurate information to the decision-maker, but also to make responsible decisions about what information should be prioritized in their reports and analyses and presented at ‘eye level’.

The more planners can learn about how people, both as individuals and groups, process information and make decisions, the better equipped they will be to promote sound decision-making—not by imposing our own preferences about policy and urban futures, but by following Thaler and Sunstein’s ideal of “influenc[ing] choices in a way that will make choosers better off, as judged by themselves.” The planner’s responsibility is not to trick people into decisions that match our normative visions of good city-building, but to help them avoid regrets and make decisions they will be able to judge as appropriate in the future. Structured decision making techniques put this into action at the level of large-scale decision processes, helping people tackle complex and unfamiliar choices with long-term consequences (Gregory, Fischhoff, & McDaniels, 2005). Equally important, however, are choices at the micro-scale of how ordinary people choose to inhabit and navigate the city each day. As this thesis has sought to demonstrate in the domain of active travel, behavioral economics has much to say about how messaging, policy, and technology can encourage people to make choices that enhance their own well-being and the well-being of their communities.

7.4 Future Research

Alongside the studies presented in Chapter 5, a number of avenues for future research drawing on this platform exist.

7.4.1 Broader Samples and Travel Surveys

The samples used in the experiments described in this thesis are all based on self-selected samples, either of BTWW participants, students, or AMT workers. These samples provide useful information on how
users with a pre-existing interest in active travel may respond to this type of behavioral intervention. However, a broad understanding of the effectiveness of behavioral interventions should be based on tests with users across the spectrum of pre-existing interest, motivation, and engagement with active modes in their daily lives.

A better understanding of the relationship between motivation and intervention effectiveness can be gained through random samples that achieve a greater degree of representativeness of urban populations. Using activity tracking apps as a data-gathering instrument in household travel surveys might be one way to achieve a broader sample of travelers in a defined jurisdiction. By requesting that households randomly selected to participate in travel surveys use an activity tracking app rather than completing travel diaries, the agency conducting the survey receives significantly more detailed data about the user’s travel patterns with less user burden, as well as an approximately random sample of active travel data.

A significant barrier to this approach is the still-limited population of smartphone users. 59% of urban adults in the United States own a smartphone today, which is sufficient to gather useful data from non-representative samples but poses significant challenges when representative datasets are needed. In order to implement smartphone-based data gathering on a large scale, more research is needed on the comparability of data derived from activity tracking apps and activity-based travel diaries, in order to determine what level of smartphone adoption is needed for a mobile activity tracking approach to become viable. However, as the availability of smartphones, public acceptance of mobile data-gathering, and normalization two-way communication between users and government entities all increase, large-scale experiments on the effects of behavioral interventions among randomized populations may become feasible. As different cities and regions begin to adopt this approach, efforts should be made to ensure that the data collected from different platforms and study types are as comparable as possible, allowing implementations and experiments conducted in different places to be easily compared or aggregated.
7.4.2 Combining Activity Tracking and Other Data Sources

While activity tracking apps are an excellent source of data on users’ active travel patterns, their ability to reliably distinguish between automotive and transit trips remains limited. However, transit smartcards provide a highly complementary source of data, especially in systems with tap-on/tap-off schemes that require passengers to swipe or wave their card when boarding and alighting from transit vehicles (Bagchi & White, 2005). This provides a precise description of the user’s trip on board transit; if combined with data from an activity tracking app tied to the smartcard account. A system of this kind could provide a comprehensive and ongoing description of the user’s entire range of travel behavior, including transit, automotive, cycling, and walking. Such a rich dataset could be used to test highly nuanced hypotheses about the interplay of demographic characteristics, home and work locations, time use, and transportation behavior.

7.4.3 Program and Infrastructure Evaluation

In addition to measuring the effect of behaviorally-inspired marketing and communications strategies such as the feedback reports used in Chapters 4 and 5, mobile activity tracking apps can be used to gather data on how cyclists and pedestrians change their behavior in response to both programming and investments in infrastructure. As apps like Moves and the supporting data-gathering infrastructure become common, active travel advocates, municipalities, and RTAs can all use this system to test how the introduction of various interventions change behavior.

The most significant obstacle to this approach is the need to attract a sufficiently large group of activity tracking users independently of the program to be evaluated. Because a randomized test of the effectiveness of a given program requires a control group, the app must be distributed to groups of users who are not receiving the intervention to be tested. The favorable user reactions to Moves observed in our studies suggests that the activity tracker itself could be implemented as a program, followed by later phases with different interventions.
Evaluations that might be conducted in this way include tests of how short-term interventions, such as “bike to work” or “bike to school” events that last for a day, week, or month, affect longer-term commuting behavior, and determinations of how cost-effective prizes or other incentives are at increasing active travel. It might also be used to examine the impact of investments such as end-of-trip facilities for cyclists, such as sheltered and secured bicycle parking, showers, and changing rooms.

Beyond school or workplace-based interventions, samples of active travelers in defined geographical areas where new cycling or pedestrian infrastructure is being built can provide an excellent means of determining how new paths, sidewalks, or protected lanes are being used, as well as the demographic characteristics of their users. The system might also allow analysts to determine whether usage of this infrastructure is the result of route changes in existing trips, or if it is in fact generating new trips.

7.4.4 Verification and Enforcement of Incentive Programs

A significant impediment to incentive-based programs for changing travel behavior is that measuring and verifying a participant’s behavior can be difficult and costly. A program that provides a monetary incentive—whether a direct payment, a prize draw, or a discount on some related expense (ranging from parking fees to health insurance payments)—risks attracting users who will misrepresent their behavior in order to obtain the benefit, reducing the cost-effectiveness of the program. This problem has been observed in a carpooling incentive program in Minneapolis, Minnesota. The program provides those who carpool with at least one other person three times per week with heavily discounted parking passes for use in a set of parking structures at the periphery of the central business district (Hill, 2013). However, because both carpool and non-carpool drivers use these ramps, it is infeasible for attendants to verify whether or not a participant is carpooling as often as they claim to.
Using an activity tracking app could allow for easy verification of the behavior of users in carpool incentive programs. Users would designate each other through a web-based interface as carpooling partners and use *Moves* or a similar app while driving each day. A script could then examine each user’s location and trip records in relation to those of their designated partners; if their trips line up (within a reasonable margin of error), they will be counted towards the user’s eligibility in the program. A verification system of this kind could eliminate cheating in carpooling incentive programs, ensuring that money spent on subsidized parking does, in fact, reduce the number of vehicles on the road and accomplish the congestion mitigation, health, and sustainability goals of the program.

7.4.5 Open Data Access and Visualization

The behavioral feedback report format described in Chapters 3 and 4 provides a number of ways for researchers and program managers to provide different sets of data to their users. However, this approach puts the decision of what data to provide in the hands of the administrator, not the end-user. An alternative approach could be a web or app-based platform that would allow full access to a user’s own data through a suite of visualization tools, as well as a supply of carefully anonymized or abstracted data for comparison purposes. Allowing users, other researchers, and interested third parties access to this data could produce new comparisons and analyses, as well as serving as powerful recruiting tool for users with an interest in understanding more about how their behavior fits into larger trends in their communities. Examining how users, interested laypeople, and experts from other fields engage with this tool and dataset as citizen scientists (Silvertown, 2009) can also be a powerful source of new hypotheses or design approaches to promoting sustainable and healthy transportation.


Bell, a C., Ge, K., & Popkin, B. M. (2002). The road to obesity or the path to prevention: motorized transportation and obesity in China. *Obesity research, 10*(4), 277–83. doi:10.1038/oby.2002.38


Noel, P. J., & Bordoff, J. E. (2008). *Pay as You Drive Auto Insurance: A simple way to reduce driving-related harms and increase equity*.


APPENDIX: SAMPLE QUESTIONNAIRES

I. Pre-Study Questionnaire

Welcome to the Active Commuting Study! This study is conducted by the Travel Behavior and Transportation Policy group at the University of British Columbia. We’re investigating how people use feedback on their commute and travel patterns from a mobile app, and would like you invite you to participate if you're 18 or older, are participating in the Twin Cities Bike Walk Week, and use an iPhone (any model) on a day-to-day basis.

To get started, we'll ask you a few questions about you and your commute in this survey. Then we'll show you how to install the Moves app and start using it to record how you get around. You should be ready to get started recording your activity in **10 minutes or less!**

Your participation is entirely voluntary and you may refuse to participate or withdraw from the study at any time. Further information on the study and your rights as a participant is available [here](#). If the questionnaire is completed, it will be assumed that consent has been given.

1. What’s your most common mode of transportation to work or school?

   - Drive alone (including using a carshare or taxi ride alone)
   - Carpool (sharing a car trip or taxi ride with at least one other person)
   - Public transportation (including bus, streetcar, subway, or ferry)
   - Bicycling
   - Walking
   - Other (please specify)

2. How often do you bike or walk the majority of the distance to work or school?
For each: “Bike” and “Walk”]

- Almost every day
- A few times per week
- About once per week
- A few times per month
- About once per month
- A few times per year
- Never

3. If you bike or walk to work or school, for how much of the year do you do so?

[For each: “Bike” and “Walk”]

- One season (about 3 months) or less
- Two seasons (about 6 months)
- Three seasons (about 9 months)
- All year

4. If you bike to work, which best describes how you feel about cycling on roads and lanes shared with vehicle traffic?

- I’m very confident in my ability to cycle in traffic
- I’m able and willing to cycle in traffic, but will use separated lanes or quiet streets when they’re easily available
- I’m able to cycle in traffic, but will use separated lanes or quiet streets unless I have no other choice
- I’m not willing to cycle in traffic and will only use separated lanes or quiet streets when I’m cycling
5. What factors are most important to you in choosing how to commute? (Pick up to 3)

- It’s reliable
- It’s fast, convenient, or fits my schedule
- It’s comfortable or a pleasant experience
- It’s affordable or lower cost
- It fits my image or lifestyle
- It reduces my environmental impact or energy consumption
- It helps me exercise or improve my health
- It’s the only option I have

6. If you drive to work at least occasionally, what's the current odometer reading (kilometers driven) on the vehicle you use most often?

(We'll ask this again at the end of the study, in order to calculate how many kilometers you've driven between now and then. If it's not convenient to check your vehicle's odometer right now, that's fine--we'll send you a follow-up survey in the next day or so; the next time you're in your vehicle, please jot down the number that the odometer is showing. If you never drive to work, don't worry about this!)

- I don’t drive to work
- I drive but can’t check my odometer right now
- I drive and my vehicle’s odometer shows: ________________________

7. Are you…

- Male
- Female
- Other
8. What’s your age?

- Under 18
- 18 to 25
- 26 to 35
- 36 to 45
- 46 to 55
- 56 to 65
- Over 65

9. How important do you feel protecting the environment (such as natural resources, biodiversity, and the climate) is compared to other public issues?

- Much more important
- Somewhat more important
- About as important as other issues
- Somewhat less important
- Much less important
- I’m not sure

10. Some people believe that protecting the environment is the responsibility of individual actions and initiative, while others believe that the government should be responsible for setting regulations and policy to protect the environment. Do you believe that environmental protection is...

- Mostly an individual responsibility
- More of an individual responsibility, but government should have a role
- Equal parts individual and government responsibility
- More a government responsibility, but individuals should have a role
• Mostly a government responsibility
• I’m not sure

GOAL SETTING

[Test group only] 11. The first step to making active commuting part of your routine is setting an achievable goal for yourself. Thinking about your commute, schedule, and lifestyle, which of the following goals for mixing cycling or walking into your weekly routine best suit you?

• Add two or more cycling or walking trips each week
• Add one cycling or walking trip each week
• Add one cycling or walking trip every other week
• Add one cycling or walking trip each month
• None of the above

[Test group only] 12. In order to make the active commuting goal above part of your routine, take a moment to think about when cycling or walking to work or school will fit into your routine best, and what changes—if any—you might need to make at home or at work to make biking or walking as easy and enjoyable as possible. Let us know what your plan is below—a few short sentences are fine.

• I’m not able to make a plan today
• My plan is…
  [Free response]

13. Lastly, we'll need the primary email associated with the iPhone you'll be installing the Moves app on. We'll use this to make sure that we know the commute reports you send are yours. Your email will be kept totally confidential, and we'll never share it with anyone.

__________________________
II. Post-Study Questionnaire

Thank you again for your participation in the Active Commuting Study. We'd appreciate your feedback on the following questions about your experiences in this study.

1. What are the best features of Moves and the feedback reports you’ve received?

   [Free response]

2. What are the least useful features of Moves and the feedback reports you’ve received?

   [Free response]

3. Since Bike Walk Week, have you…

   - Begun biking or walking to work or school more frequently?
   - Begun biking or walking to do errands, visit friends or family, or for pleasure more frequently?
   - Found better biking or walking routes to work, school, or other places you go?
   - Purchased equipment to improve your biking or walking commute (such as a bicycle, bicycle accessories, a bikeshare membership, walking shoes, or outerwear)?
   - Walked or biked with a family member, friend, or coworker?

4. Since Bike Walk Week, have you talked with friends, family, or coworkers about commuting in general, walking or cycling, or Moves?

   - Yes, and I mentioned or showed them Moves or a feedback report
   - Yes, but I didn’t mention Moves
   - No

Any comments?
[Free response]

5. Do you plan to continue using *Moves* on your iPhone?

- Yes, I plan to continue using *Moves*
- No, I like the app but have had problems with battery consumption or other issues
- No, I don’t like the app or don’t find it useful

Any comments?

[Free response]

6. The Active Commuting Study will be piloting a new system in the next few weeks that will allow us to give you feedback without requiring you to report your commuting time manually. We're very excited about this program and hope it can provide you with more information for less work on your end!

If you'd like to participate and continue receiving occasional feedback reports, please indicate this below:

- Yes, I would like to keep participating in Active Commuting Study projects
- No, don’t contact me about any more Active Commuting Study projects

*Thanks again for participating in the Active Commuting Study! Happy travels!*