The Role of Implementation Intentions for Cue Detection, Habit Strength, and Behaviour Change

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Abstract

Lifestyle behaviour change and habit formation interventions have been implemented in various health contexts for many decades, including physical activity and eating behavioural interventions. Self-regulatory tools such as implementation intentions (if-then plans) are one of the most commonly used techniques in these interventions. Implementation intentions are concrete action plans that specify, in an if-then format, when, where, and how one will act in order to achieve a specific goal ("If situation Y occurs, then I will initiate goal-directed behaviour X!"). Their effectiveness has been demonstrated for a wide range of populations, conditions, settings, and behaviours, and thus they have become widespread as a result. Most studies thus far have examined behaviour change as direct outcomes, however, psychological mechanisms (namely, cue detection and habit strength) that lead to the behaviour change has received little attention in research. Also, most studies in this domain were conducted in either controlled lab settings or they were short interventions in field settings. Therefore, behaviour change and habit formation interventions with longer duration in field settings that examine the psychological mechanisms leading to behaviour change need to be conducted. Implementation intentions have been shown to lead to more accurate and faster cue detection as well as increasing habit strength, but *how* this occurs requires further investigation. To our knowledge, no study to date has examined the separate effects of the individual cue (if-part) and response (then-part) components of implementation intentions on cue detection and habit strength, respectively. As a result, there remain gaps in our knowledge on the essential role of implementation intentions in the changes in cue detection and habit strength in longitudinal lifestyle behavioural interventions. The current research sought to shed light on these questions using data collected from the McGill CHIP Healthy Weight Program, a year-long behavioural weight loss intervention. We examined how implementation intentions influence cue detection and habit strength, leading to physical activity and eating/drinking behaviour changes and weight loss. One hundred and seventy-two participants enrolled in the intervention completed measures of cue detection and habit strength and reported their tracking of physical activity and food/drink consumption at various time points. Their weight was measured at each session throughout the intervention. Collected from the eighty-three participants in the experimental condition of the intervention, the physical activity and eating/drinking behaviour-related if-then plans were coded for their specificity. Results from multilevel analyses (reported in two studies) suggest that physical activity and eating/drinking cue detection and habit strength were not associated with average physical activity steps or calorie/fat consumption, respectively. Greater response specificity in eating/drinking if-then plans lead to greater healthy eating/drinking habit strength, and greater cue detection lead to greater cue specificity in subsequent eating/drinking if-then plans. These findings and their clinical relevance as well as limitations and directions for future research are discussed.

Résumé

Des interventions sur les changements comportementaux dans le mode de vie et la formation des habitudes ont été mises en œuvre dans divers contextes de santé depuis de nombreuses décennies, comprenant des activités physiques et des interventions comportementales lié à l'alimentation. Des outils d'autorégulation tels que les « intentions de mises en forme » (plans si-alors) sont une des techniques les plus couramment utilisées dans ces interventions. Ces intentions de mises en forme sont des plans d'action concrets, au format si-alors, spécifiant quand, où et comment une personne doit agir pour atteindre un objectif spécifique (« Si la situation Y se produit, alors j'engagerai un comportement en vue d'atteindre le but X! »). Leurs efficacités ont été démontrées pour un large éventail de populations, de conditions, de paramètres et de comportements et se sont ainsi généralisés en conséquence. Jusqu'à aujourd'hui, la majorité des études ont examiné les changements comportementaux en tant que conséquences directes. Cependant, peu d'attention a été portée sur les mécanismes psychologiques (à savoir, la détection des signaux et la force des habitudes) qui conduisent à ce changement de comportement. De plus, beaucoup d'études dans le domaine ont été menées en laboratoires contrôlés ou au travers de courtes interventions sur le terrain. Ainsi, des interventions sur les changements comportementaux dans le mode de vie et la formation des habitudes doivent être menées sur le terrain et sur de plus longue durée, afin d'examiner ces mécanismes. Il a été démontré que les intentions de mises en œuvre conduisaient à une détection des signaux plus précise et plus rapide ainsi qu'à renforcer les habitudes, mais une recherche plus approfondie sur le « comment » est nécessaire. À notre connaissance, aucune étude à ce jour n'a examiné les effets distincts des composantes des intentions de mise en œuvre (la composante « signal » (partie « si ») et la composante « réponse » (partie « alors »)) sur la détection des signaux et la force des habitudes. Par conséquent, il reste des lacunes dans notre connaissance sur le rôle essentiel des intentions de mise en œuvre dans les changements de la détection des signaux et de la force des habitudes lors d'interventions comportementales sur le mode de vie. La recherche actuelle cherche à éclaircir ces questions à l'aide de données recueillies dans le cadre du Programme poids santé CHIP McGill, une intervention comportementale, longue d'un an, sur la perte de poids. Nous avons examiné comment les intentions de mise en œuvre influencent la détection des signaux et la force des habitudes, conduisant à des changements de comportement sur l'activité physique et l'alimentation et à la perte de poids. Cent soixante-douze participants ont effectué des mesures de détection des signaux et de force des habitudes et ont reporté le suivi de leur activité physique et consommation d'aliments et boissons à diverses périodes de l'intervention. Leurs poids étaient mesurés à chaque séance de l'intervention. Recueillies auprès des quatre-vingt-trois participants à la condition expérimentale de l'intervention, l'activité physique et le comportement lié à l'alimentation et boisson, en lien avec les plans « si-alors », étaient codifiés selon leurs spécificités. Les résultats d'analyses multi-niveaux (rapportés dans deux articles) suggèrent une absence de lien entre la détection des signaux (pour l'alimentation, boisson et activité physique) et la force des habitudes avec le niveau d'activité physique et la consommation de calories/lipides moyens. Une plus grande spécificité dans la composante « réponse » des plans si-alors pour l'alimentation et boisson conduit à renforcer l'habitude de manger et boire sainement. Une meilleure détection des signaux conduit à une plus grande spécificité de signaux dans les plans si-alors pour l'alimentation et boisson subséquents. Ces résultats et leurs pertinences cliniques, ainsi que leurs limitations et instructions pour la recherche future, sont discutés.

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Contributions of Authors

This dissertation consists of two manuscripts of which I am the first author. Both manuscripts are in preparation for submission, and both are co-authored by me, Gentiana Sadikaj, Aleksandra Luszczynska, & Bärbel Knäuper. The initial conceptualization of the two studies integrated into the RCT (presented in this dissertation), generation of research questions, and creation of measurement questionnaire items were done by me with the help of all lab members in brainstorming and refining them during various lab meetings. I further elaborated the hypotheses and study design before we began administering the questionnaires that we designed to participants in the McGill CHIP Healthy Weight Program, a year-long longitudinal behaviour change intervention. I was the first research coordinator of this intervention and wrote the REB application and amendments under the supervision of Bärbel Knäuper. My dissertation research questions and data collection were integrated into the intervention. Eight graduate student coaches and I ran 25 intervention groups at the McGill downtown campus and the CHIP clinic locations. Data collection was undertaken for a period of four years completed by me, the other graduate student coaches, undergraduate group and research assistants, my successive research coordinators, and the staff at our collaborating clinic the McGill Comprehensive Health Improvement Program (CHIP). Data organization, double-checking and verification, and cleaning took place for another year completed by me, undergraduate research assistants, and the research coordinators. Gentiana Sadikaj and I ran all of the statistical analyses for both manuscripts. The results were interpreted by me, Gentiana Sadikaj, with the help of all co-authors. I wrote the first draft of both manuscripts with the help of Gentiana Sadikaj. Bärbel Knäuper significantly contributed to editing both manuscripts. Preliminary results reported in this dissertation have been presented at the Canadian Psychological Association conventions, 2017 in Toronto, ON and 2018 in Montreal, QC; the International Society of Behavioral

Nutrition and Physical Activity (ISBNPA), 2017 in Victoria, BC; and the Canadian Society for Psychomotor Learning and Sport Psychology (SCAPPS), 2016 in Waterloo, ON.

Chapter 1: Introduction and Background

Human behaviour is an important determinant of health, and thus behaviour change interventions play a pivotal role in health and well-being. There has been abundant research on the development of behaviour change interventions for various behaviour outcomes, such as weight loss, eating and physical activity behaviours, medication adherence, lifestyle management, cell phone use, use of contraception, and smoking cessation (Adriaanse, de Ridder, & Wit, 2009; Belanger-Gravel, Godin, & Amireault, 2013; Benyamini et al., 2013; Elliston, Ferguson, Schüz, & Schüz, 2017; Mistry, Sweet, Rhodes, & Latimer-Cheung, 2015; Scott-Sheldon, Huedo-Medina, Warren, Johnson, & Carey, 2011; van Osch, Lechner, Reubsaet, Wigger, & de Vries, 2008). Vast resources have been invested in interventions aimed at individuals, communities, and populations based on an abundant source of theories and methods for intervention design and evaluation. Hundreds of behaviour change interventions are being delivered per day (Michie, 2018). However, most of these interventions (including a wide variety of biomedical studies and behaviour change interventions) have modest effects and 40 to 89% of them were found to be incomplete, unusable, and non-replicable (Glasziou et al., 2014). Recommendations from Glasziou and colleagues emphasized the need for high quality and complete reporting of all aspects of interventions, allowing researchers to better organize and synthesize complex research evidence and make inferences that generate new understanding. Therefore, we need to improve behaviour change interventions by improving comprehension of the reasons for their variation and to reduce waste in research. Standardized reporting guidelines on active components that make interventions effective are essential.

Significant advances have been made in behaviour change research over the past few decades, including standardization and improvement of intervention reporting and their underlying theory (Michie et al., 2018). However, reporting of behavioural interventions was still vague, inconsistent with varying terminology, and lacking detail in existing studies (Michie & Johnston, 2012). Without the use of the same terms used to describe the same things, terms that are consistent and understood by all, researchers are limited in their ability to replicate, evaluate, improve, and implement effective interventions. As a result, Michie and colleagues created a taxonomy of techniques for designing, evaluating, and reporting behaviour change interventions, namely behaviour change techniques (Michie, Johnston, & Carey, 2016; Michie et al., 2013).

Behaviour Change Techniques (BCTs) in Behaviour Change Interventions

Behaviour change techniques (BCTs) are "active ingredients" designed to change behaviour within an intervention. Specifically, they are discrete, low-level components of an intervention that on their own have the potential to change behaviour. They must also be observable and replicable (Michie, Johnston, & Carey, 2016). Examples of BCTs include goal setting and action planning such as implementation intentions. In collaboration with hundreds of multidisciplinary experts around the world, Michie and colleagues developed an extensive hierarchically structured taxonomy of techniques (BCTs) used in behaviour change interventions, namely "BCT taxonomy v1 (BCTTv1)" (Michie et al., 2013). In this project, labels and definitions of BCTs were rated and then grouped according to similarity of the active ingredients in the selected interventions. This resulted in 93 consensually agreed, distinct, precise, and well-defined BCTs classified into 16 groups. These individual BCTs can be used alone or in combination with other BCTs in behaviour change interventions (Michie & Johnston, 2012).

BCTTv1 was developed by international experts from varied behavioural domains, which include psychology, behavioural medicine, and health promotion from seven different countries. Thus, this taxonomy can be used with confidence and is highly relevant across a range of disciplines, countries, and populations from which they were drawn. Namely, BCTTv1 integrated various cross-behaviour BCT taxonomies (Abraham & Michie, 2008; Michie, Johnston, Francis, Hardeman, & Eccles, 2008) and several behaviour-specific taxonomies for physical activity, alcohol use, smoking, and condom use (Abraham, Good, Huedo-Medina, Warren, & Johnson, 2012; Michie et al., 2011; Michie, Hyder, Walia, & West, 2011; Michie et al., 2012). BCTTv1 has been used to code interventions in a wide range of health behavioural domains, such as physical activity and dietary behaviours, oral hygiene behaviours, hazardous drinking, sexual health behaviours, blood pressure control and management behaviours, diabetes preventative behaviours, and antibiotic-prescribing behaviours (Newbury-Birch et al., 2014; Po'e, Heerman, Mistry, & Barkin, 2013; Schwarzer, Antoniuk, & Gholami, 2015; Young et al., 2014).

In summary, conceptualizing interventions using BCTs enables the possibility of identifying “active ingredients” of behaviour change interventions, which can then lead to improving the efficacy of interventions. In BCTTv1, labels and definitions of BCTs are well-organized, clear, and precise with no overlapping terms or redundancy. Moreover, they apply to an extensive range of behaviour change interventions and are organized into a hierarchical structure, which can aide recall by organizing the wide range of BCTs into “chunks”. Specifying and classifying BCTs have transformed methods for reporting the content of these interventions, allowing greater consistency and clarity in research. However, to better understand how BCTs in interventions lead to behaviour change, mechanisms of action (MoAs) through which BCTs have their effect require further research. Linking BCTs to MoAs from behavioural theory allows researchers to investigate and assess the processes behind effective interventions, and in turn help them learn how to design interventions that effectively target specific behaviours and populations.

Linking Behaviour Change Techniques (BCTs) with Mechanisms of Action (MoAs)

MoAs are theoretical constructs that explain the process by which behaviour change occurs. To further comprehend this process, the need to apply extensive and systematic theory to the design of interventions are increasingly acknowledged in research. Studies that investigated the association between theoretically sound combinations of BCTs and intervention efficacy have shown that theory-based interventions are more effective. Some examples include findings that show the number of BCTs used did not predict intervention efficacy but having a theoretical basis for the intervention did (Dombrowski et al., 2012). Dombrowski and colleagues also found that interventions with more BCTs that were congruent with a specific theory associated with greater weight loss in obese adult patients. Furthermore, Taylor and colleagues found that the more that worksite physical activity interventions were based on theory, the greater their efficacy (Taylor, Conner, & Lawton, 2012). These results were confirmed by similar findings in other populations and delivery modes (Michie, Abraham, Whittington, McAteer, & Gupta, 2009; Webb, Joseph, Yardley, & Michie, 2010).

Ideally, behaviour change interventions are all theory-based and specify key constructs that explain processes of change, namely how, when, and why change occurs. The implementation of theory also allows researchers to investigate why certain inventions succeed while others fail. Therefore, future research should apply theoretical principles to designing successful interventions. Theoretical frameworks have been developed to address this challenge and to make theories more accessible to an interdisciplinary audience (Cane, O'Connor, & Michie, 2012; Michie et al., 2005). Although there are integrative frameworks, a consensus is still needed on how to link individual MoAs with the active components in BCTs. An example would be linking habit formation as a BCT with behaviour regulation as a MoA. This is especially important for developing future interventions and to test theory by evaluating interventions. For example, preliminary research to address this has been conducted in forms such as systematic literature reviews, meta-analyses associating BCTs with theory, and intervention development frameworks that provide guidance on which BCTs to select for targeting MoAs (Michie et al., 2018). More recently, based on a specific theoretical framework and additional frequently used MoA constructs from existing behaviour change theories, Carey and colleagues examined hypothesized links between BCTs and MoAs frequently described in published interventions. They identified more than two thousand BCT-MoA links between 70 BCTs and 25 MoAs, of which 87 links were statistically significant (Carey et al., 2019). Their findings showed which BCT-MoAs links are more frequently used than others and which ones are believed to be present or appear to be absent. For example, no link was identified between optimism and norms, whereas BCT prompts/cues was linked to three MoAs including behavioural cueing, environmental context/resources, and memory/attention/decision processes. Their results also highlighted the possibility that groups of BCTs and MoAs could be working together synergistically in the behaviour change process.

Implementation Intentions, Cue Detection, and Habit Formation as Effective Behaviour Change Techniques and Their Associated Mechanisms of Action

Implementation intentions are amongst one of the most used self-regulatory BCTs used in behaviour change interventions. They are concrete action plans that specify, in an if-then format, when, where, and how one will act in order to achieve a specific goal (“If situation Y occurs, then I will initiate goal-directed behaviour X!”) (Gollwitzer, 1993, 1999). These action plans have been adapted to various behavioural contexts and have been shown to be effective, although the degree of their effectiveness varies depending on the types health behaviours the reviewed studies were targeting. Those that are highly effective likely result from cognitive mechanisms of action we assume to be associated with if-then planning (Gollwitzer & Sheeran, 2006; Prestwich, Sheeran, Webb, & Gollwitzer, 2015; Webb & Sheeran, 2007). When planning details of when, where, and how to carry out a goal using implementation intentions in an if-then format, people are more accurate and faster at detecting the specified opportunity to act (Webb & Sheeran, 2004).

Accordingly, accessibility to cues is heightened and cue-response links are strengthened with the use of implementation intentions (Aarts, Dijksterhuis, & Midden, 1999; Gollwitzer, 2015; Orbell & Verplanken, 2010; Prestwich, Sheeran, Webb, & Gollwitzer, 2015; Webb & Sheeran, 2008), which are highly relevant to the BCT-MoA links found between prompts/cues (BCT) and behavioural cueing (MoA), as well as between action planning (BCT) and behavioural regulation (MoA) (Carey et al., 2019). Furthermore, the intended behavioural response should be initiated automatically upon encountering the specified cue without further conscious effort or the need to deploy further cognitive resources. With repeated enactment of this cue-response link, habits can be formed over time. Therefore, cue detection and automatic behavioural initiation, a defining characteristic of habit formation, should enable individuals to overcome self-regulatory challenges during goal striving and attainment without having further cognitive burden.

Although implementation intentions are commonly used in behaviour change interventions, more research is required to further understand the interaction between the separate “if-” and “then-” components and other MoAs including cue detection and habit strength. Specificity of the implementation intention individual components could be another potential MoA that could explain the efficacy of implementation intentions. To our knowledge, no study to date has examined this MoA, particularly in longitudinal settings. The second study of this research project will fill this gap in the literature by examining the specificity of separate components as a MoA to changes in cue detection and habit strength in a year-long behaviour lifestyle intervention. Previous research has shown that the higher the specificity in implementation intentions, particularly higher specificity in the cues of the if-component, the greater the likelihood that these implementation intention will be enacted and the target behaviour(s) will be achieved (de Vet et al., 2011; de Vet, Oenema, & Brug, 2011; Dombrowski, Endevelt, Steinberg, & Benyamini, 2016; Fleig et al., 2017; van Osch, Lechner, Reubsaet, & De Vries, 2010; Verbiest et al., 2014; Ziegelmann, Lippke, & Schwarzer, 2006). Taken together, understanding MoAs that are linked to BCTs used in the present research, namely cue detection and habit strength linking to implementation intentions, are fundamental in delivering effective health behaviour change interventions.

Purpose of Research and Overview of Hypotheses

The purpose of this research was to address certain gaps in previous research to further understand underlying processes and mechanisms that drive behaviour change. Although many studies to date have focused on behaviour change as targeted primary outcomes, fewer have examined the role of psychological factors such as cue detection and habit strength that may lead to behaviour change. Thus, the first objective of this research was to investigate the process by which changes in habit formation components (cue detection and habit strength) translate into behaviour changes associated with weight loss. It was hypothesized that at the within-person level, all cross-lagged relationships between the four variables will be significant. At the between-person level, it was hypothesized that cue detection and habit strength will increase, whereas average calorie intake will decrease, and physical activity steps will increase, which will lead to weight loss. This is addressed in the first study (Chapter 2).

The second objective of this research was separately examining the individual components of implementation intentions (the "if" and "then" components, which were referred to as cue and response) and their relationships with cue detection and habit strength, respectively. It was hypothesized that higher levels of cue specificity are associated with higher levels of cue detection, and reciprocally, greater cue detection in turn is related to subsequent greater cue specificity for both the physical activity and eating/drinking behaviours data. Moreover, it was also hypothesized that greater response specificity is associated with greater habit strength, and reciprocally, greater habit strength in turn relates to subsequent greater response specificity for both the physical activity and eating/drinking behaviours data (Chapter 3).

In summary, the main thesis of this research project is that examining the impact of psychological factors (cue detection and habit strength) in the process of behaviour change is pertinent to understanding the mechanisms of change and that further investigation of implementation intentions' individual components is crucial to comprehending this process.

Current Study

The data for this research project originates from the McGill CHIP Healthy Weight Program, a randomized controlled trial and a year-long lifestyle behaviour change intervention. Data collection took place from 2013 to 2017 from 172 individuals participating in one of 25 groups led by different lifestyle coaches, who were trained clinical psychology doctoral students. Participants were screened and randomized into the control or experimental condition. The control condition participants received the basic 22-session weight loss intervention, while participants in the experimental condition received individual training and coaching on implementation intentions in addition to the basic intervention. All participants completed measures of cue detection, developed for this project, at varying time points throughout the intervention, along with measures of habit strength. At baseline, 3, and 12 months, they also tracked food/drink consumption and physical activity steps using a pedometer given to them at the beginning of the study, as well as their weight at every session. Two studies resulted from this data, with the first investigating the relationships between cue detection, habit strength, behaviour change (change in physical activity average steps or average calorie consumption), and weight, as presented in the first study (Chapter 2). The second study examined the relationship exclusively between the “if” component of implementation intentions and cue detection, as well as the “then” component and habit strength, as presented in the second study (Chapter 3).

Chapter 2: How Habits Are Formed: Examining Relationships Between Cue Detection, Habit Strength, and Behaviour

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Abstract

Habits are automatic behavioural responses to environmental cues based on learned context-behaviour associations (Gardner, 2010). This study is the first to examine how changes in psychological predictors (cue detection and habit strength) translate into changes in physical activity (PA), eating/drinking behaviour outcomes, and eventually weight loss. We examined these processes of change longitudinally in an intensive 12-month lifestyle behavioural and weight loss intervention. In the McGill CHIP Healthy Weight Program (N = 172), self-report questionnaires assessing cue awareness and habit strength were administered six times across 12 months, beginning monthly and then further spaced out. Calorie and fat consumption and PA average steps were assessed at baseline, 3, and 12 months through online self-reports and pedometers (PA). We found at the within-participant level that greater habit strength was associated with subsequent greater cue detection at later time points in both the physical activity and eating/drinking models. In the physical activity model, we found that higher habit strength was associated with subsequent lower weight at later time points as well. As hypothesized for between-participant level paths, cue detection, habit strength, and average PA steps increased, while average calorie consumption and weight decreased over time. These results suggest that cue detection and habit strength have an important role in the process leading to behaviour change.

Keywords: cue detection; habit strength; behaviour change intervention; eating/drinking behaviours; physical activity behaviours

Introduction

Overweight and obesity are among the leading preventable causes of death in the world (Blüher, 2019). They may lead to health complications and significantly increase an individual's risk for premature death from chronic diseases, such as cardiovascular diseases (e.g., stroke and heart attack), type 2 diabetes, hypertension, and some forms of cancer (WHO, 2018). Overweight and obesity cast a heavy burden on the health care system because an estimated 1.9 billion adults worldwide have overweight or obesity (WHO, 2018).

Changing maladaptive eating and physical activity habits that lead to weight gain and forming new healthier habits are critical to weight loss and maintenance. Ouellette and Wood (1998) define habits as "[behavioural] tendencies to repeat responses given a stable supporting context" (p. 55). This definition stipulates that specific cues have to be repeatedly displayed and followed by associated behavioural responses in order for the cue-response connection to develop and thus for a habit to form. Forming if-then plans (implementation intentions) is an example of a technique that supports this habit formation process: If-then plans connect specific cues with adaptive behavioural responses (Gollwitzer, 1993, 1999). They specify, in an if-then contingency format when, where, and how one will act to achieve a specific goal ("If situation Y occurs, then I will initiate goal-directed behaviour X!" (Gollwitzer, 1993, 1999; Gollwitzer & Sheeran, 2006). For example, "If I see my running shoes by the door, then I will put them on and go for a run". If-then plans allow the situational cues to trigger the pre-defined goal-directed response. This pre-defined goal-directed response is elicited automatically whenever the cues are encountered (Gollwitzer, 1999). If-then planning has been found to be an effective strategy to change maladaptive eating and physical activity habits that lead to weight gain (Adriaanse, de Ridder, & de Wit, 2009; Adriaanse, Vinkers, De Ridder, Hox & De Wit, 2011; Benyamini et al., 2013; de Vet, Oenema, & Brug, 2011; Kroese, Adriaanse, Evers, & De Ridder, 2011). The purpose of the present study is to examine the process by which changes in habit formation components (cue detection and habit strength) translate into behaviour changes associated with weight loss.

Cue Detection

Cues that elicit eating behaviours range from external sensory cues (e.g., visual cues including appearance, proximity, visibility, and accessibility, olfactory and gustatory cues) to cognitive and internal cues (e.g., emotional and physiological) (Coelho, Idler, Werle, & Jansen, 2011; Elliston, Ferguson, Schüz, & Schüz, 2017; Fedoroff, Polivy, & Herman, 1997; Gaillet, Sulmont-Rossé, Issanchou, Chabanet, & Chambaron, 2013; LeGoff & Spigelman, 1987; Piqueras-Fiszman, Alcaide, Roura, & Spence, 2012; Spence, 2018; Wadhera & Capaldi-Phillips, 2014; Zellner, Lankford, Ambrose, & Locher, 2010). In the present studies, cues can be defined as external environmental cues or internal physiological, emotional, or cognitive cues associated with eating/drinking or physical activity behaviours. Effects of cues on initiating eating behaviours can be seen in everyday life, particularly those of visual cues. In fact, visual cues are the most influential on food consumption and perception, given that the first sensory contact with food is mostly through the eyes (Wadhera & Capaldi-Phillips, 2014). For example, a piece of strawberry-flavored mousse presented on a white plate was judged to be more flavorful, sweeter, and palatable than the same food placed on a black plate (Piqueras-Fiszman, Alcaide, Roura, & Spence, 2012). External cues may elicit associated eating behaviours, including the overconsumption of food and problematic snacking behaviours (Bilman, van Kleef, & van Trijp, 2017; Elliston, Ferguson, Schüz, & Schüz, 2017; Johnson, 2013; Schaefer & Magnuson, 2014; Schüz, Schüz, & Ferguson, 2015).

Becoming more aware of cues may elicit adaptive health behaviours. For example, using olfactory food cues (i.e., fruity odours) may lead individuals to choose starters with vegetables and desserts with fruits (Gaillet, Sulmont-Rossé, Issanchou, Chabanet, & Chambaron, 2013). Environmental cues (i.e., priming dietary goals) may enhance self-regulation in tempting food situations, and result in reduced food intake (Papies & Hamstra, 2010). In parallel, exposure to environmental cues has been shown to lead to increased time spent on physical activity (Hepler, Wang, & Albarracin, 2012) and conscious activation of exercise goals has been shown to increase an individual's amount of exercise (Iso-Ahola & Miller, 2016). It has also been demonstrated that more consistent people, activity, routine, location, time, and mood cues upon initiation of physical activity behaviours are linked to greater physical activity automaticity (Pimm et al., 2016). In general, environmental cues have strong eliciting effects on both eating and physical activity behaviours. Eating and physical activity cues result in the execution of eating and physical activity behavioural responses, which may be adaptive or maladaptive. Forming (new) if-then contingencies is a technique to activate cues and build new, adaptive habits.

In the present studies, cue detection is defined as the degree to which a cue in one's internal/external environment is consciously perceived by the individual. Before habits can form and strengthen, individuals must become consciously aware of and notice their cues. In other words, one must notice the cues first to be able to elicit a behavioural response. Without consciously detecting the cues, no external behaviour or internal responses can be prompted and thus, the automatic cue-response contingency that lead to habit formation cannot be elicited.

Habits

Researchers have distinguished between habit as a behaviour and habit as a process or psychological construct (Hagger, 2018). When defined as a behaviour, habit may be measured using past behavioural frequency, which assumes that repeating the same behaviour frequently leads to the formation of habitual action (Hagger, 2018; Sutton, 1994; Trafimow & Borrie, 1999; Triandis, 1977). However, repeated action does not necessarily lead to habit formation, and thus measuring habit using past behavioural frequency has its limitations in inferring habit formation (Gardner, 2012). Habit may be defined as habitual actions that are linked to cues and contextual features that can trigger a set of responses without conscious awareness (Aarts & Dijksterhuis, 2000; Gardner, 2015; Hagger, 2018; Mazar & Wood, 2018; Verplanken & Orbell, 2003; Wood, 2017; Wood & Rünger, 2016). Thus, habit formation is not dependent on past behavioural frequency. In fact, learned automatic responses do not need to be frequently performed. Even when contextual cues are rarely encountered, the cue-response contingency may still be activated regardless (Gardner, 2012). For example, weekly churchgoers enact the habit of saying ‘amen’ at the conclusion of public prayer on a weekly basis. For those who attend religious services only at Christmas, they would also say ‘amen’ despite not attending on a regular basis. The behaviour is automatic in both instances, but their frequency differs drastically (Gardner, 2012). One could argue that there may be social influence (e.g., others around them saying ‘amen’), which may be the case during public prayer, but people are likely to say ‘amen’ when praying alone without external influences. Therefore, automaticity should be seen as the “active ingredient” of a habit and repetition frequency as its “precursor and possible consequence” (Gardner, 2012). In sum, automaticity is the key component to habit formation, not the frequency of exhibiting the behaviour. Psychological factors that contribute to strengthening automaticity of a behaviour in habit formation should be investigated. In fact, the goal of the present study aims to examine whether change in eating and physical activity cue detection will lead to strengthened habit strength, which we hypothesize will lead to behaviour change.

If-Then Plans (Implementations Intentions)

An if-then plan contains two components, the first being the “IF” component, which contains the cues and the second being the “THEN” component, which contains the external or internal actions to be elicited (Gollwitzer, 1993, 1999). External actions refer to behaviours or action responses that one can carry out, such as walking or eating an apple. Internal actions refer to cognitive or emotional responses, including reminding oneself to do something, encouraging oneself, and challenging negative thoughts. Forming if-then plan has been found to be much more effective than solely relying on willpower or motivation, as expressed in intentions (“I will do X!”). In fact, a large meta-analysis found medium-to large effects of if-then plans on goal achievement across many behaviour domains (94 studies, d = .65) (Adriaanse, de Ridder, & Evers, 2011; Gollwitzer & Sheeran, 2006) and studies with longer follow-ups ranging from six months up to two years showed that the formed habits are strong and durable (Chapman & Armitage, 2010; Conner & Higgins, 2010; Luszczynska, Scholz, & Sutton, 2007; Luszczynska, Tryburcy, & Schwarzer, 2007; Prestwich et al., 2005). Forming if-then plans results in an increased cue detection and – due to the linguistic if-then contingency – a strengthening of the link between the cues and the (adaptive) response. If-then planning leads to habit formation because a cue-response contingency is created, rendering the new behavioural response automatic (Webb & Sheeran, 2004). This occurs because firstly, if-then plans specify the exact cues in the “IF” component for which a behavioural response is needed (Webb & Sheeran, 2004), thereby activating them and making it more noticeable in the environment. Secondly, the if-then contingency format is assumed to establish a strong mental association between these critical cues and a previously actively chosen behavioral response (Oettingen, Honig, & Gollwitzer, 2000). Furthermore, research has shown that habit-formation interventions using if-then plans help individuals form “higher-order habits” that target complex behaviours, which is particularly applicable in a health context (Phillips, Johnson, & More, 2019). The eating/drinking and physical activity goals targeted in our intervention referred to complex health behaviours and can be seen as higher-order goals, which means that they can be executed in more than one way.

Cue Detection and Habit Formation Training in the McGill CHIP Healthy Weight Program

In the present study, we investigated the roles of changes in reported cue detection and habit strength over time on eating and physical activity behaviours and weight loss in the McGill CHIP Healthy Weight Program (HWP), a year-long lifestyle behavioral intervention and randomized controlled trial. In both conditions of the HWP, coaches trained participants to become more aware of both their internal and external cues that trigger adaptive and maladaptive eating and physical activity behaviours and to replace the maladaptive responses with adaptive ones. In the if-then plan condition, participants were additionally taught by their coaches to create explicit if-then plans, namely using the identified cues in the “IF” component and connecting them to an adaptive action plan in the “THEN” component and writing down their plans on an if-then plans sheet that was weekly updated with the coach.

Participants in both conditions lost large amounts of weight (an average of 9.98% of their initial body weight) and no differences between conditions were found for weight loss success or maintenance (Knäuper et al., 2018). Potential reasons for a lack of between-group differences in weight loss could be that participants in both conditions were trained to become more aware of their internal and external cues and to create responses to these cues. The only difference between the two conditions was that the enriched condition participants were taught explicitly how to link their identified cues and prepared action responses together in an if-then format by writing them down, whereas the control condition participants learned implicitly through goal-oriented action plans that were part of the DPP. Thus, the two conditions were very similar, and their data were used together in the present study.

We adapted the Diabetes Prevention Program (group-DPP) manual for the present study and both control and if-then plan conditions received the basic DPP treatment. In the manual, two entire sessions were dedicated to teaching participants how to identify problematic cues and add positive food, physical activity, and social cues to one's environment. Participants in both conditions were taught how to connect these cues with adaptive eating and physical activity behaviours. At the end of both sessions, participants were guided by their group coach in identifying problematic as well as positive cues and in creating concrete action plans (when, where, how) to react to the cues in a goal-congruent way. For example, participants were guided by their coach to identify and change problematic social cues with an action plan (e.g., identifying what he/she will do, when it will be done, obstacles that could potentially be encountered, how to overcome obstacles, how to increase the likelihood of success in carrying out this action plan).

Methods

The design and methodology of this study are described in detail in the published study protocol (Knäuper et al., 2014). Data collection took place from 2013 to 2017. Individuals with overweight or obesity (BMI of 28 to 45 kg/m^2, waist circumference $\geq$ 88 centimeters for women, $\geq$ 102 centimeters for men, 18 to 75 years of age) were eligible if they engaged in less than 200 minutes of self-reported moderate or vigorous physical activity per week. The full list of exclusion criteria, participant recruitment methods, steps for determining eligibility, study procedures, and the intervention details are included in the published study protocol (Knäuper et al., 2014) and the reports of the effects of the intervention on the main outcomes (Knäuper et al., 2018; Knäuper et al., 2019).

Participants

A total of 864 individuals completed the initial screening and 208 were randomized, out of which 172 participants received the intervention. The final sample size from which data were analyzed was 172 participants. Table 1 shows the demographic information of all participants. A CONSORT flow diagram of the progress through the phases of the trial, dropout analysis, and detailed demographic information are provided in Knäuper et al. (2018).

Measures

Cue Detection

Cue detection for lack of physical activity. Cue detection for lack of physical activity was assessed with two questions developed for the purpose of the present study (“I notice when I sit for too long” and “I notice what keeps me from exercising [e.g., weather, fatigue, busy schedule, lack of motivation]”). The correlation of these two questions was $r = .37$, $p < .001$ at baseline and $r = .41$, $p < .001$ at 2.5 months. For every question, participants were asked to rate the degree to which they notice these cues on a 7-point Likert-type rating scale that ranged from 1 (disagree) to 7 (agree).

Eating/drinking cue detection. The eating/drinking cue detection was measured with five questions, developed for the purpose of the present study (1) “I notice when I am doing something else while I am eating. (e.g., watching TV, using the internet).” (2) “While I am eating or drinking, I notice what and how much I consume”, (3) “I notice how much food I put on my plate”, (4) “I notice when there is junk food in my house”, and (5) “I noticed when I am stressed or feeling down”. The internal consistency was α = .70 at baseline and α = .61 at 2.5 months.

Habit Strength

Using the 4-item Self-Report Behavioural Automaticity Index (SRBAI) (Gardner, 2012; Gardner, Abraham, Lally, & Bruijn, 2012), seven behaviours were examined in this questionnaire to measure habit strength, which correspond to the seven cues on the cue detection questionnaire. Specifically, the two physical activity behaviours and five eating/drinking behaviours on the SRBAI correspond to the two physical activity cues and five eating/drinking cues on the cue detection questionnaire, respectively. The SRBAI is a short version of the 12-item Self-Report Habit Index (SRHI) (Verplanken & Orbell, 2003) that retains only the four items that assess automaticity. These items are “I do automatically”, “I do without having to consciously remember”, “I do without thinking”, and “I start doing before I realize I’m doing it”. A Likert-type rating scale ranging from 1 (disagree) to 7 (agree) was provided to rate each of the 12 behaviours.

Physical activity habit strength. Two physical activity behaviours were used to analyze change in physical activity habit strength: “spending more time moving instead of sitting’’ and “exercising for at least 150 minutes per week”, which correspond to the two cues used to assess cue detection for lack of physical activity: “I notice when I sit for too long” and “I notice what keeps me from exercising (e.g., weather, fatigue, busy schedule, lack of motivation)”, respectively. Habit strength for each of the two behaviors was assessed via the 4-item Self-Report Behavioural Automaticity Index (SRBAI) (Gardner, 2012; Gardner, Abraham, Lally, & Bruijn, 2012), e.g. “I do automatically”. The items were rated on a Likert-type rating scale ranging from 1 (disagree) to 7 (agree). The correlation between these two behaviours was *r*

= .54, $p < .001$ at baseline and $r = .59$, $p < .001$ at 3 months. The mean score was calculated by averaging the scores of the four automaticity items of these two behaviours at baseline and at the 3-month time point, respectively.

Eating/drinking habit strength. Change in eating/drinking habit strength was assessed for five behaviours on the SRBAI related to eating/drinking, which correspond to five cues examined in the eating/drinking cue detection subscale (see Table 2). Internal consistency $\alpha = .67$ at baseline and $\alpha = .79$ at 3 months. The eating/drinking habit strength mean scores at baseline and 3-month time points were computed by averaging the scores across the four automaticity items for all five questions at each time point.

Physical Activity Steps. Physical activity was assessed using PiezoRD® pedometers (StepsCount, Ontario, Canada). The pedometers have been validated for steps and intensity related physical activity in real-life conditions (O'Brien, Wojcik, D'Entremont, & Fowles, 2018). Participants were asked to wear their pedometer at all times from the time they wake up in the morning until they go to bed for seven consecutive days before the study began (baseline), at 3-month, and then at 12-month time points when the intervention ended. They were instructed to wear the pedometer at all times except when sleeping and during physical activities in water because the pedometer is not waterproof. Before removing it every night, they were instructed to record their pedometer steps on myhealthcheckup.ca, a physical activity tracking website maintained by CHIP. For physical activity that persisted for 10 minutes or longer at moderate or vigorous intensities, participants were asked to track the duration and type of activity on myhealthcheckup.ca from a dropdown list of activity options (e.g., stationary biking at moderate or vigorous intensity for 20 minutes). The reason for tracking was to capture their physical activity duration, type, and intensity so that it can be converted into equivalent pedometer steps using a steps equivalency calculation table developed by our collaborator, the Comprehensive Health Improvement Program (CHIP) clinic. Then the number of steps recorded directly from the pedometer each day was added to the converted steps to calculate the total steps of the day. Average scores of the total number of steps were calculated for the seven consecutive days of physical activity tracking at the 3- and 12-month time points. Because participants were asked to always wear the pedometer, “double counting” steps could occur. However, consistent tracking rules were emphasized to all participants, thus “double counting” steps did not have an impact on examining the overall pattern of change in physical activity amount.

Calorie and Fat Consumption. Data on calorie and fat consumption were extracted from food tracking diaries that participants kept/entered online (either on the app/website “eatracker.ca”, a website developed by the organization Dieticians of Canada, on “myfitnesspal.com"), or on paper. Earlier intervention group participants were asked to track using eatracker.ca and participants in later groups used myfitnesspal.com and/or its mobile application version for those with smartphones. Participants were asked to record their daily food and beverage consumption for a week prior to baseline, 3-, and 12-month time points. Because calorie and fat consumption are highly related and show the same consumption patterns, we conducted the analyses with only calorie consumption data.

Questionnaire Administration and Measurement Time Points

We administered both the cue detection and habit strength questionnaires at baseline. Cue detection was afterwards assessed at 0.5, 1.5, 2.5, 5, and 11 months. Habit strength was assessed again at 1, 2, 3, 6, and 12 months. We were expecting the greatest changes in cue detection and habit strength to occur during the initial 3-month intensive teaching period of the program, during which weekly sessions in the first 2.5 months for cue detection and the first 3 months of habit strength occur. In the analyses, cue detection at baseline, 1.5, 2.5, and 5 months are represented by cue detection time 0 to 3. Habit strength at baseline, 2, 3, and 6 months are represented by habit strength time 0 to 3.

From these time points, we chose to examine how the increase in cue detection and habit strength over this core period of the program predicts later changes in behaviours and weight outcomes. Average physical activity steps and average calorie/fat consumption were measured at baseline, 3-, and 12-month time points, which are represented as average steps/calories time 0 to 2. Weight was measured at each of the 22 sessions. Corresponding to the period we chose to examine for cue detection and habit strength, we chose to focus on the effects of change in average calorie/fat consumption from baseline to 3 months (time 0 to 1) and from 3 to 12 months (time 1 to 2) in the present study. The effects on weight were examined at the same time points, namely from baseline to 3 months (weight time 0 to 1), and then from 3 to 12 months (weight time 1 to 2). The time points used in the present study are shown in bold print in Figure 1.

Hypotheses

The present study examines how changes in certain psychological factors, namely cue detection and habit strength, lead to adaptive eating and physical activity behaviour changes and weight loss. At the between-person level, we hypothesize that cue detection and habit strength will increase throughout the initial 6-month observation period, whereas average calorie intake will decrease (in the eating/drinking behaviours model) and physical activity steps will increase (in the physical activity behaviours model) in the 12-month treatment period, which will lead to weight loss.

At the within-person level, we hypothesize that all cross-lagged relationships between cue detection, habit strength and eating/drinking behaviours, and weight displayed in Figure 2a will be significant as hypothesized. Namely, higher cue detection should lead to subsequent higher habit strength, which would lead to more physical activity steps and less calorie consumption, resulting in eventual weight loss. Higher habit strength should also lead to subsequent higher cue detection, rendering the relationship between habit strength and cue detection to be bi-directional. We also hypothesize that autoregressive paths of cue detection, habit strength, and average steps measured at a previous time point will be positively associated with the same respective variables measured at the subsequent time points. Equivalently, we hypothesize that average calorie intake at the previous time point will be negatively associated average calorie intake at the subsequent time point. Finally, we hypothesize that lower average calorie intake and/or a higher number of physical activity steps will result in weight loss.

Analytic Strategy

In the present study, we used the autoregressive latent trajectory model with structured residuals (ALT model) (Bollen & Curran, 2004; Curran & Bollen, 2001; Curran, Howard, Bainter, Lane, & McGinley, 2014) to examine the relationships between cue detection, habit strength, average physical activity steps or average calorie consumption, and weight loss, as well as how each of these variables individually and jointly progress over the 12-month treatment period. The ALT model combines elements of latent curve modeling with time-specific relations that examine growth and change process of variables of interest. An important aspect of the ALT model is that the growth and change process is disaggregated at the between-person (person-specific) and within-person (time-specific) levels. Between-person differences represent how the stability and change in the variable of interest over time vary between individuals, whereas within-person differences measure how the variable remains stable or changes within an individual over time (i.e., comparing the same measure at two different time points of the same individual). Furthermore, using multivariate ALT, it is possible to model how between-person and within-person change processes covary over time. Specifically, in the present study, we are interested in examining the cross-lagged relationships between cue detection, habit strength, average physical activity steps (in the physical activity model), or average calorie intake (in eating/drinking model) at both the between-person and within-person levels.

Model building proceeded as following. First, the parameters of (i.e., intercepts, linear slopes, quadratic slopes) latent growth curves were estimated using the observed repeated measures of cue detection, habit strength, average physical activity steps (or average calorie intake), respectively. The variances of these growth curve parameters were set to be random (i.e., varying across individuals) and covariances among them were estimated. The variances of the growth curve parameters indicate the extent to which individuals among each other in initial starting point and the rate of change in each variable. The covariances indicate the extent to which these growth curve parameters covary within individuals (e.g., an individual's initial starting point – intercept – is related to the individual's linear rate of change). When found to be not statistically different from zero, the variances of these growth parameters were fixed to 0.

The residuals, which represent the deviations of the observed repeated measures from the expected score given the underlying growth curve trajectory, were modeled as follows. Autoregressive paths were added between pairs of successive residuals (e.g., the residual of cue detection at 5 months was regressed on the residual of cue detection at 2.5 months). These autoregressive paths represent relationships between pairs of successive residuals unaccounted for by the underlying growth trajectory.

Next, cross-lagged regression paths between pairs of successive residuals between all four variables were added. Cross-lagged paths from cue detection to subsequent habit strength and from habit strength to subsequent cue detection, as well as bidirectional paths between the remaining variables were added because we expected the all variables to mutually influence each other. Therefore, cross-lagged paths in both directions were tested to capture the natural process of mutual influence of these paths in real life. First, the cross-lagged regression paths between cue detection and habit strength were added such that cue detection at time 1 to 3 were regressed on the residuals of habit strength time 1 to 3, respectively. Simultaneously, paths from habit strength residuals at time 1 to 3 were regressed on cue detection at time 1 to 3, respectively. Subsequently, residuals were also used to construct cross-lagged regression paths between the remaining three variables of habit strength, average steps (or average calorie intake), and weight. The estimates of these cross-lagged regression paths represent prospective influences of one variable on the other variable within an individual. For example, higher-than-average eating/drinking habit strength at time 1 is associated with a higher-than-average eating/drinking cue detection at time 2.

Using Mplus 8.3 (Muthén & Muthén, 2019), autoregressive latent trajectory (ALT) model analyses were conducted. In the physical activity model, results showed that 37.79% of participants had complete data in all the variables used in the model, while 19.77% had missing data in one variable, and the remaining individuals showed missing data in two or more variables. In the calorie consumption model, it was found that 41.28% of participants had complete data in all the variables used, while 15.12% of participants had missing data in one variable, and the remaining participants had missing data in two or more variables.

Little's MCAR test (Little, 1988) showed that data were missing completely at random for variables in both calorie consumption and physical activity models (χ^2 = 97.58, *df* = 87, *p* = .21 in the change in calorie consumption model; χ^2 = 99.45, *df* = 93, *p* = .31 in the change in physical activity model). Missing data were handled with full information maximum-likelihood estimation (FIML), which allowed participants with some missing data to be included in the analyses.

Differences in autoregressive regression path estimates across time points were examined by comparing the fit of a model in which the path estimates were permitted to differ across time points with the fit of a model in which the estimates were restricted to be equal across these time points. Model comparison was conducted using the rescaled -2 log likelihood difference test, which is distributed as chi-squared with degrees of freedom equal to the rescaled difference in the number of parameters between models (Satorra & Bentler, 2010). An α value of .05 was used to determine whether these path estimates differed across time points. Pooled estimates are subsequently reported when no difference across time points in these autoregressive path estimates was found. The same strategy was used to examine differences across time points in the cross-lagged path estimates.

Model fit of the final models was evaluated with the following fit indices: chi-square value, the Comparative Fit Index (CFI > .90 are satisfactory values), and the Root Mean Square Error of Approximation (RMSEA < .08 are satisfactory values), Tucker Luis Index (TLI > .90), and Standardized Root Mean Square Residual (SRMR < .08 are satisfactory values). (Hooper, Coughlan, & Mullen, 2008; Hu & Bentler, 1999; MacCallum, Browne, & Sugawara, 1996; Steiger, 2007; West, Taylor, & Wu, 2012).

Results

Model 1: Physical Activity Autoregressive Latent Trajectory (ALT) Model

The fit of this model was good, as shown in the fit statistics section indicated in Table 3. At the between-person level, a linear increase in physical activity cue detection was found, and the increase decelerated over time as shown by a negative quadratic slope estimate (see Table 3 for detailed estimates under the section of mean scores). A similar pattern of change was found in physical activity habit strength. Namely, a linear increase was found, and it decelerated over the treatment period. As for the average physical activity steps, a relatively greater linear increase was also found with deceleration over time. In the weight variable, a linear decrease was found as shown by its negative linear slope estimate, and its decrease accelerated over time according to its positive quadratic slope estimate. The variances of the linear growth slopes of all four variables were not different from zero, suggesting no individual differences in the rate of the linear changes in the physical activity cue detection, habit strength, average steps, and weight, respectively. For the sake of conciseness, only significant covariances among intercepts and slopes of the growth curves will be reported in this section and in the results tables. The covariance between physical activity habit strength intercept and physical activity average steps intercept was significant with a positive estimate, suggesting that individuals who showed a greater increase in physical activity also showed a greater increase in physical activity average steps. Furthermore, the covariance between the physical activity steps intercept and weight was significant with a negative estimate, which suggests that individuals who showed a greater increase in physical activity steps also showed a reduction in weight.

At the within-person level, the estimates of autoregressive paths from physical activity cue detection at a previous time point to cue detection at the subsequent time point were not significant between all four time points. Secondly, the estimate of autoregressive paths from physical activity habit strength from baseline to the 2-month time point (time 0 to 1) was not significant. However, the estimates of autoregressive paths between the remaining time points from 2 to 3 months (time 1 to 2) and from 3 to 6 months (time 2 to 3) were both significant. They were not statistically different from each other. These results indicate that between 2 to 6 months (time 1 to 3) in the treatment period, higher levels of physical activity habit strength at a previous time point were associated with higher levels of habit strength at the subsequent time point. Thirdly, the estimates of autoregressive paths between the three time points at which average physical activity steps were measured (time 0 to 2: baseline, 3, and 12 months) were not significant. Finally, autoregressive path estimates between the three time points at which weight was measured were marginally significant. The estimate was larger between baseline and 3 months (time 0 to 1) compared to the estimate between 3 and 6 months. Detailed results of the autoregressive relations can be found in Figure 2 and 3, and Table 3 (see "autoregressive effects").

The cross-lagged estimates of physical activity cue detection at 2.5 and 5 months (time 2 to 3) regressed on physical activity habit strength at 2 and 3 months (time 1 and 2), respectively, were significant. The remaining cross-lagged paths were all not significant. Higher levels of physical activity habit strength at a preceding time point were associated with higher levels of physical activity cue detection at the subsequent time point at these time points (see Figures 2 and 3, as well as Table 3 referring to "cross-lagged effects" for further detail).

Model 2: Eating/Drinking Autoregressive Latent Trajectory (ALT) Model

Model fit for the final eating/drinking ALT model was satisfactory, which is supported by results under the fit statistics section shown in Table 4. At the between-person level, it was found that eating/drinking cue detection increased linearly as shown by a positive linear slope (see "*M*" scores in Table 4). However, its rate of linear increase decreased over time as indicated by a negative quadratic slope. It was also found that eating/drinking habit strength increased linearly, indicated by a positive linear slope, and its rate of increase accelerated over the treatment period as shown by a positive quadratic slope. Furthermore, we found that average calorie intake and weight both decreased over the treatment period.

At the within-person level, two autoregressive paths between three successive measurements of eating/drinking habit strength were significant. Specifically, eating/drinking habit strength at 1.5 and 3 months (time 1 and 2) were positively associated with habit strength at 3 to 6 months (time 2 to 3), respectively. No statistical difference between these estimates were found. The remaining autoregressive paths within eating/drinking habit strength and the other three variables in the model were not significant (see Table 4, see “autoregressive effects”).

Several cross-lagged relationships from eating/drinking habit strength to cue detection, as well as from habit strength to weight were significant. Namely, eating/drinking cue detection at 2.5 and 5 months (time 2 and 3) regressed on eating/drinking habit strength at 1.5 and 3 months (time 1 and 2) were significant, respectively. There was no statistical difference among these estimates. Moreover, weight at 3 and 12 months (time 1 and 2) regressed on eating/drinking habit strength at 1.5 and 6 months were significant, respectively. These estimates also had no statistical difference. All remaining cross-lagged paths that we examined in the eating/drinking behaviours model were not significant. Refer to Table 4 to inquire further (see “cross-lagged effects”). Table 5 and 6 display the descriptive statistics and correlations for the variables used in the physical activity and eating/drinking behaviours models, respectively.

Discussion

The present study investigates the influence of cue detection and habit strength on eating and physical activity behaviour change, and how they lead to weight loss. Data collected from the McGill CHIP Healthy Weight Program, a year-long lifestyle intervention and randomized controlled trial were analyzed. The goal of this study was to examine how certain psychological factors may be linked to behaviour, and as a result to weight loss longitudinally in a real-life environment.

Taken together, in both the physical activity and eating/drinking models, greater habit strength led to greater cue detection at later time points. Theoretically, we anticipated that as people notice their surrounding cues more, their habits would subsequently become more automatic and stronger. We also expected the reciprocal cross-lagged relationship of greater habit strength leading to subsequent greater cue detection to be reinforced throughout the intervention. The reason that we hypothesized the cross-lagged relationships to be bidirectional is that the paths in both directions are closely intertwined and reinforce each other.

The association of each path with one another is highly complex. It may be difficult and theoretically unjustifiable to disentangle them to determine which variable was the initial predictor leading to the other variable as the outcome. Analyzing these cross-lagged paths together captures the natural process of these bidirectional relationships in real life. As a result, we hypothesized that the effects between cue detection and habit strength could be bidirectional. We expected participants to learn to consciously detect cues first in order to enact the automatic cue-response contingency in habit formation. They were specifically trained to detect their cues, especially during the first three months of weekly core teaching sessions. It would take time for participants to develop these trained skills, which could explain why the relationship between cue detection and habit strength was not significant between time points at the beginning of the intervention (i.e., baseline, 1.5, and 2 months). At the beginning of the intervention, participants may not be as good at detecting their cues in contrast with the later period of the intervention (e.g., when they reached 2 to 3 months time points). The results showed that over time, as habit strength increased, cue detection increased accordingly, indicating that habit strength became the main force that drove the process in both physical activity and eating/drinking models. Perhaps, people's need to consciously detect cues decreased as habits became more automatic over time. By the end of the core teaching period of 3 months, participants developed better cue detection skills. With their habits already formed, they may no longer need to detect cues as much.

Nonetheless, habit maintenance is challenging. At times, various participants encountered slips and reverted to their old eating/drinking or sedentary habits. Subsequently, the coaches trained them to reapply their old if-then plans to help them recover and form new habits again. Even after participants recovered from their slips and solidified their new habits, coaches encouraged them to remain vigilant of their cues throughout the intervention. Hence, automaticity of the cue-response contingency is not a panacea for habit formation. If-then planning is important and highly beneficial over the long-term for reinforcing the relationship between cue detection and habit strength.

Although results showed greater habit strength predicting greater cue detection, the remaining question becomes why greater cue detection was not associated with greater habit strength in the hypothesized bidirectional relationship. A possible reason is that there may be potential mediators or moderators that could explain the missing link. For example, self-efficacy could be a psychological factor that serves as a mediator such that the better cue detection could be associated with higher self-efficacy, which would then lead to greater habit strength.

In the eating/drinking behaviours model, higher levels of habit strength were also associated with weight loss at later time points, indicating that habit strength is also a driving force toward the final outcome of weight loss. These findings showed the overall importance of habit strength in the intervention. Although the effects between habit strength and weight loss was significant, the results did not show the anticipated effect between habit strength and average calorie consumption, neither did any effect show between average calorie consumption and weight loss. Additionally, in the physical activity model, results revealed no association between habit strength, average physical activity steps, and weight loss. Abundant research has shown that weight loss results as a combination of reducing calorie/fat consumption and increasing physical activity in various populations (Butler, Black, Blue, & Gretebeck, 2004; Goodpaster et al., 2010; Jakicic, Wing, & Winters-Hart, 2002; Kruger, Blanck, & Gillespie, 2006) . Therefore, the mechanism of change from increasing habit strength to weight loss must be related to behaviour change, namely increasing physical activity steps and/or reducing calorie/fat consumption. A potential reason for the missing link between habit strength and weight loss could be that the change in eating, drinking, and physical activity behaviours may not have been reflected by people's tracking of their food/drink consumption and physical activity steps a week prior to the three chosen time points of measurement (baseline, 3, and 12 months). Perhaps, mandatory tracking may need to occur longer than a week prior to each time point to accurately reflect behaviour change. Another reason could be that tracking through self-report may not be a reliable method of measurement, possibly due to people tracking much later than the time of food/drink consumption, causing recall bias. Finally, a third potential reason could be that people may have intentionally under-reported their food/drink consumption due to feelings of guilt or embarrassment, and hence skewing the results of analyses.

Regarding some non-supported links between cue detection and habit strength, a potential reason could be that there may be more suitable drinking/eating behaviours that reflect behaviour change for losing weight than the ones we chose in the cue detection and habit strength questionnaires. Examples of the eating/drinking behaviours that we selected include reducing portion size and lowering emotional eating. There may have been other eating/drinking behaviours that could be more influential on weight loss, such as reducing grazing/picking behaviours, regular meal patterns, or conscious attempts to regulate food intake based on perceived hunger (e.g., stop eating when full). Before selecting the five eating/drinking behaviours, we thoroughly reviewed the literature for empirical evidence that would demonstrate which target eating behaviours are most relevant to successful weight loss, but found that no such evidence yet exists (Carter & Jansen, 2012). Therefore, we selected five eating/drinking behaviours based on the most targeted and emphasized eating behaviours in the DPP manual.

Our first chosen time point for cue detection is at 1.5 months and the first for habit strength is at 2 months. Regarding the potential issue of overlapping between time points in cue detection and habit strength, it is logical to presume that change in cue detection can predict change in habit strength, even if there is some overlap in the time period between baseline to 1.5 months in cue detection and baseline to 2 months in habit strength. In studies that examined the cue-action association, it has been shown that when the cue and action are highly associated, “relatively spontaneous delivery of the intended action upon noticing the target cue” occurs in prospective memory performance tasks (Albiński, Kliegel, & Gurynowicz, 2016; McDaniel & Einstein, 2000). In these tasks, individuals switch attention from the ongoing task to thinking about the intended action and then performing it within a very short period of time (McDaniel & Einstein, 2000). For example, when people are on their way home from work, they may see the cue of "grocery store". This visual cue can lead to going grocery shopping. Upon triggering the cue, the subsequent action response can be elicited very quickly. Therefore, increase in cue detection from baseline to 1.5 months and the resulting increase in habit strength also from baseline to 2 months can occur within approximately the same time frame and do not need to be lagged in time.

As for time points of measurement used in the present study, the reason that not all time points at which variables were measured were included in our analyses is that we selected the most critical time points to examine, which can provide more theoretical meaningful results to explain the process that led to behaviour change and weight loss. During earlier time points, we excluded cue detection data measured at 0.5 months and habit strength data at 1 month. The reason was that we estimated the temporal distance from baseline to 0.5 or 1 month to be too short for changes in cue detection and habit formation to occur. Any differences measured between baseline and 0.5 or 1 month could be due to measurement error.

During later time points, we excluded cue detection at 11 months and habit strength at 12 months. We focused on the first 6 months of the intervention for the two psychological variables, given the frequency of the measurement during this period. Specifically, to examine change in a given variable, the interval time between assessment points and the number of assessment points must be proportional to the expected rate of change in the variable (Ebner-Priemer & Trull, 2012). Evidence suggests that individuals who exercised at a gym can develop activity habits in the first five weeks (Armitage, 2005) and that it takes 18 to 254 days, with an average time of 66 days to form eating, drinking, and physical activity habits (Lally, Van Jaarsveld, Potts, & Wardle, 2010). Therefore, we examined change in habit strength and cue detection by utilizing the measurements obtained in the first 6 months of the study. Therefore, increasing the complexity of the model by including all time points was not theoretically sound and not justified nor necessary analytically.

Limitations and Future Directions

In the present study, we created a questionnaire that measures cue detection because no questionnaire existed in the literature. This questionnaire contained only two items referring to physical activity, resulting in low internal consistency for this subscale. Thus, caution should be exercised when interpreting the results of the path model. The two physical activity items in the questionnaire measure lack of physical activity, specifically whether participants notice when they have not been physically active for a while and whether certain obstacles get in the way of physical activity. In future research in which cue detection will be assessed, a few additional physical activity-related items assessing conscious awareness of specific physical activity cues (e.g., visual cues like packed gym bag beside bed) would be beneficial.

In the eating/drinking subscale of the habit strength questionnaire, our purpose was to examine whether there was reduction or cessation of the unhealthy eating/drinking behaviours, and to measure whether the reduction or cessation was maintained throughout the intervention. Therefore, the behaviours were mostly ‘non-behaviours’ (e.g., not eating while doing something else). In future research, adding additional items that focus on ‘doing-behaviours’ that measure healthy eating/drinking habit strength (e.g., eating fruits or vegetables) could be useful. Moreover, if the items that measure reduction or cessation of unhealthy eating/drinking behaviours can be rephrased in ways that measure ‘doing-behaviours’, then this could also be beneficial.

Another limitation to items measuring ‘non-behaviours’ is that participants may have been confused with double negatives in the questions. For example, “not eating large quantities of high fat/calorie foods” is the behaviour and participants were asked to rate on a Likert-type rating scale of “I do automatically” or “I do without thinking”. It was challenging to phrase these items in a way that measures what we were attempting to measure, and at the same time avoiding double negatives.

On the other hand, a strength of the cue detection questionnaire is that the physical activity and eating/drinking behaviour items were matched with items that assessed the exact same behaviours on the habit strength questionnaire. Furthermore, several of the eating/drinking behaviours items on the questionnaires were also closely matched with the primary and secondary outcomes of the study, such as the item that measured consumption of high fat/calorie foods matching the change in average fat and calorie intake outcome, and the item that measured lack of physical activity matching the change in total physical activity step equivalents (see Supplementary Materials in the Appendix A). The behaviours that the items featured were all physical activity and eating/drinking behaviours that were targeted, taught, and emphasized in the present study. Given the longitudinal nature of our intervention, these items allow the assessment of habit change over time.

In addition to improving measurements used, data collection methodology can also be further improved for future research. Aside from physical activity steps measured by pedometers, we collected the remaining data through participants' self-report given that it was the optimal and most cost-effective methodology at the time. For tracking of food and drink consumption, future studies should take advantage of ecological momentary assessment (EMA) methodologies (Shiffman, Stone, & Hufford, 2008) that involve repeated sampling of eating and drinking behaviours in real time in people's daily life environments. Although we encouraged participants to record on paper or directly in their tracking application (for those who owned smart phones) their food and drink intake as soon as possible, there may have been participants who waited for longer periods of time to write down or record the information online (on the tracking cell phone app or the tracking websites). A suitable EMA tool could be electronic devices such as electronic bracelets or watches that can send auditory or text reminders to participants regularly throughout the day to record their food consumption retake. Regular reminders would increase the likelihood of people tracking what they consumed right away, minimizing recall bias and maximizing ecological validity.

Despite these limitations, taken together, our findings provide empirical support for the essential role of habit strength in health behavioural interventions and further our understanding of the mechanism by which psychological variables, namely cue detection and habit strength, lead to behaviour change, and ultimately the outcome of weight loss. Specifically, findings suggest that higher habit strength lead to higher cue detection in both physical activity and eating/drinking models, and that higher habit strength lead to lower weight in the eating/drinking model.

Months	**0**	**0.5**	**1**	**1.5**	**2**	**2.5**	**3**	**4**	**5**	**6**	**11**	**12**
Cue Detection (CD)	**CD**	CD		CD		**CD**			CD		CD	
Habit Strength (HS)	**HS**		HS		HS		**HS**			HS		HS
Average Calorie/Fat Consumption (CAL/FAT)	**CAL/FAT**						**CAL/FAT**					**CAL/FAT**
Average Physical Activity Steps (PA)	**PA**						**PA**					**PA**
Weight (W)	**W**	W	W	W	W	W	**W**	W	W	W	W	**W**

Figure 1. Measurement timeline of variables in the cross-lagged model analyses.

a)

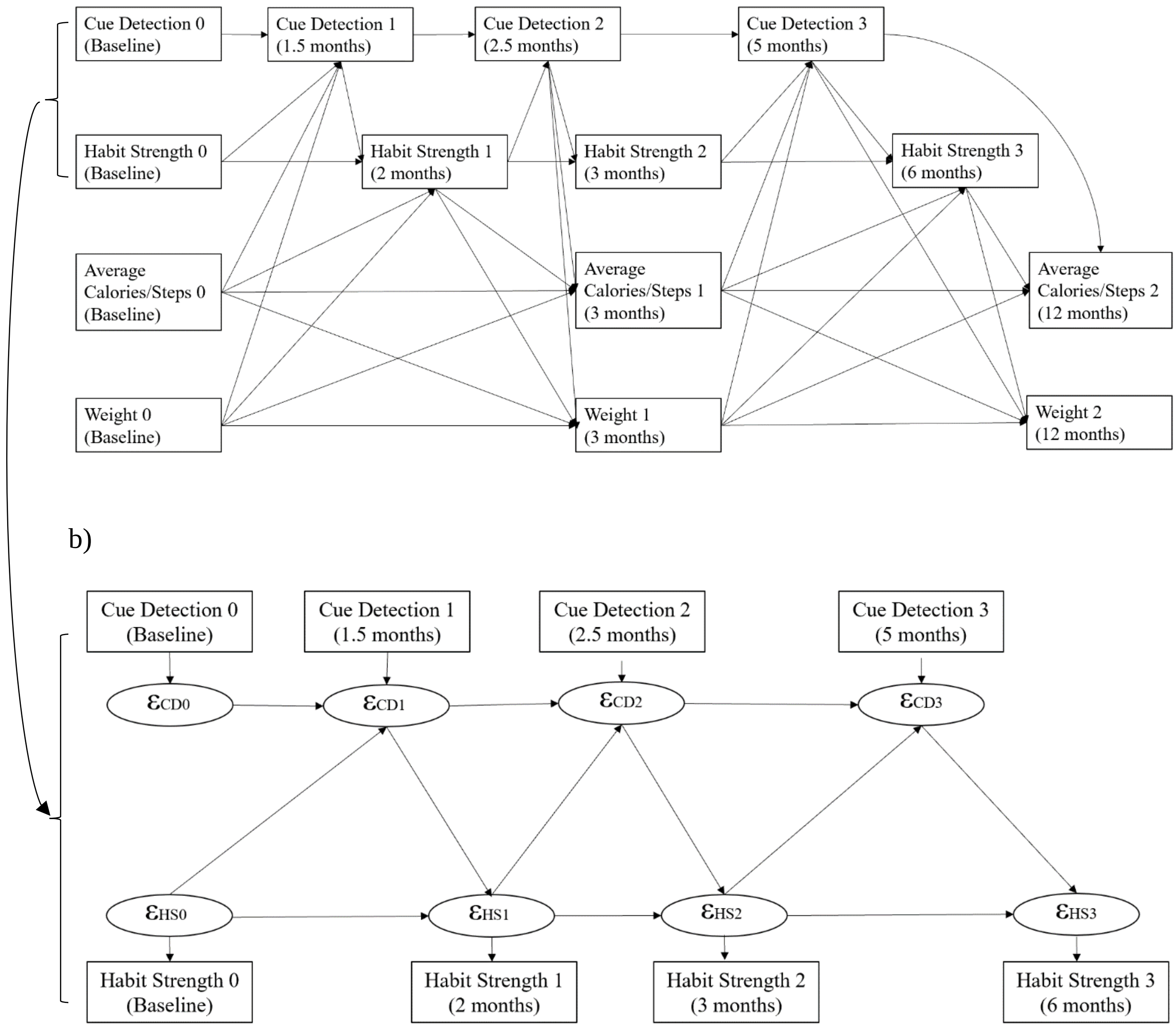

Figure 2a. Autoregressive latent trajectory model with structured residuals demonstrating cross-lagged and autoregressive relationships examined between cue detection, habit strength, average calorie consumption (in the eating/drinking behaviours model) or average physical activity steps (in the physical activity model), and weight. In Figure 2b, “Habit Strength 0” to “Habit Strength 4” are observed habit strength average scores. ε_{HS0} to ε_{HS4} indicate standard residuals of habit

strength. Specific time points for habit strength are indicated in brackets in each observed score. Due to the complexity of the model, residual scores are not shown for every variable involved. Only residuals of cue detection and habit strength are shown in Figure 2b. The same method of residuals was used to model autoregressive and cross-lagged paths between the remaining three variables. The intercepts, linear slopes, and quadratic slopes were estimated using observed repeated measures of the cue detection, habit strength, average calorie consumption (in the eating/drinking behaviours model) or average physical activity steps (in the physical activity model), and weight. The residuals represent the deviations of the observed repeated measures from the expected score given the underlying growth curve trajectory.

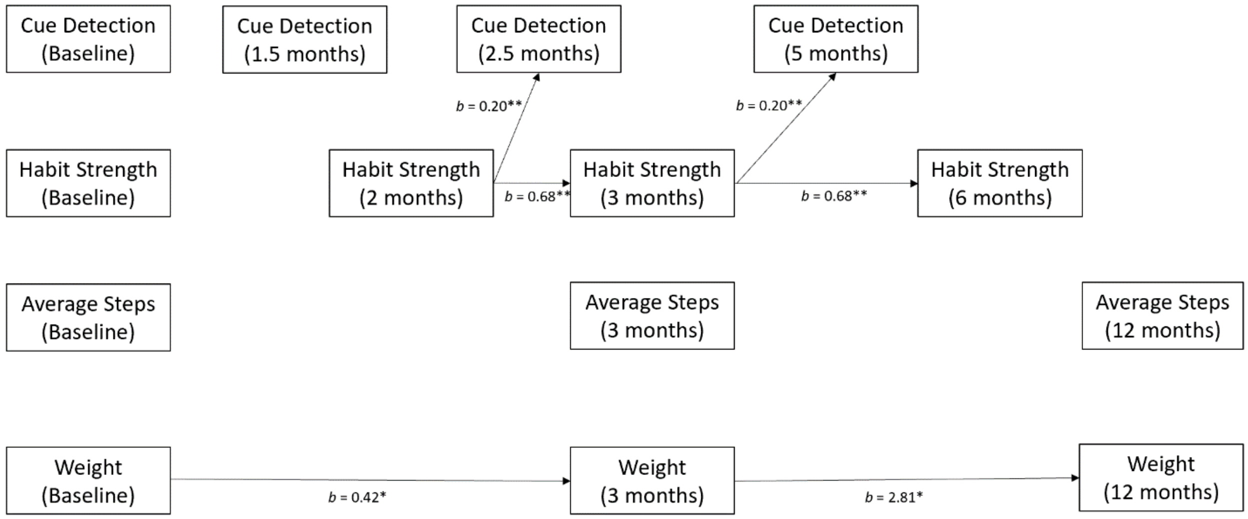

Figure 3. Significant autoregressive and cross-lagged estimates in the physical activity autoregressive latent trajectory (ALT) model. ** $p < .01$, * $p < .05$. The *b* estimates are unstandardized values.

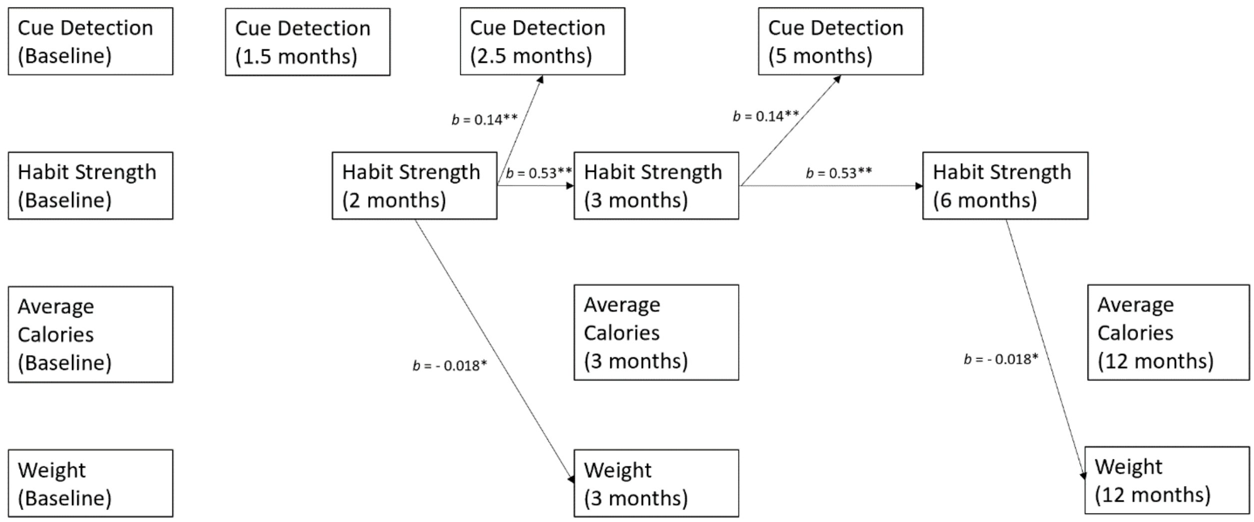

Figure 4. Significant autoregressive and cross-lagged estimates in the eating/drinking autoregressive latent trajectory (ALT) model. ** *p* < .01, * *p* < .05. The *b* estimates are unstandardized values.

Table 1. Demographics

	n = 172
Age, mean (*SD*)	50.22 (11.97)
Gender, female, *n* (%) female	138 (80.23%)
Caucasian, *n* (%)	133 (77.33%)
Married, *n* (%)	99 (57.56%)
Education, bachelor's degree *n* (%)	73 (42.44%)
Employed, *n* (%)	114 (66.28%)
Household income > $40,001, *n* (%)	117 (68.02%)
Smoker, *n* (%)	9 (5.23%)

Table 2
Eating/Drinking Cues and their Corresponding Behaviours

	Cues	**Behaviours**
(1)	"I notice when I am doing something else while I am eating. (e.g., watching TV, using the internet)."	"Not eating while doing something else"
(2)	"While I am eating or drinking, I notice what and how much I consume."	"Not eating large quantities of high fat/calorie foods"
(3)	"I notice how much food I put on my plate."	"Not eating large quantities of high fat/calorie foods"
(4)	"I notice when there is junk food in my house."	"Eating recommended portion sizes"
(5)	"I notice when I am stressed or feeling down."	"Not eating when I am stressed or feeling down"

Table 3

Physical Activity ALT Model Results

Parameter	Unstandardized Coefficient (*SE*)	Standardized Coefficient	*p*	95% CI
Autoregressive Effects				
$CD_0 \rightarrow CD_1$	0.139 (.087)	.213	.112	[-0.246, 0.009]
$CD_1 \rightarrow CD_2$	0.139 (.087)	.130	.112	[-0.032, 0.310]
$CD_2 \rightarrow CD_3$	0.139 (.087)	.138	.112	[-0.032, 0.310]
$HS_0 \rightarrow HS_1$	0.298 (.238)	.295	.210	[-0.169, 0.765]
$HS_1 \rightarrow HS_2$	0.675 (.090)**	.654	.00	[0.498, 0.852]
$HS_2 \rightarrow HS_3$	0.675 (.090)**	.584	.00	[0.498, 0.852]
$AvSteps_0 \rightarrow AvSteps_1$	- 0.020 (.491)	-.008	.967	[-0.982, 0.941]
$AvSteps_1 \rightarrow AvSteps_2$	- 0.020 (.491)	-.020	.967	[-0.982, 0.941]
$W_0 \rightarrow W_1$	0.424 (.192)*	.389	.027	[0.048, 0.801]
$W_1 \rightarrow W_2$	2.814 (1.258)*	1.190	.025	[0.350, 5.279]
Cross-lagged Effects				
$CD_1 \rightarrow HS_1$	0.058 (.316)	.331	.066	[-0.039, 1.199]
$CD_2 \rightarrow HS_2$	0.198 (.116)	.116	.090	[-0.031, 0.426]
$CD_2 \rightarrow AvSteps_1$	0.545 (1.026)	.070	.595	[-1.466, 2.556]
$CD_2 \rightarrow W_1$	- 0.001 (.009)	-.013	.885	[-0.019, 0.016]
$CD_3 \rightarrow HS_3$	0.198 (.116)	.101	.090	[-0.031, 0.426]
$CD_3 \rightarrow AvSteps_2$	0.545 (1.026)	.070	.595	[-.1.466, 2.556]
$CD_3 \rightarrow W_2$	- 0.009 (.044)	-.039	.845	[-0.096, 0.078]
$HS_0 \rightarrow CD_1$	- 0.061 (.120)	-.105	.612	[-0.295, 0.174]
$HS_1 \rightarrow CD_2$	0.199 (.076)**	.327	.009	[0.050, 0.347]
$HS_1 \rightarrow AvSteps_1$	0.264 (.445)	.056	.553	[-0.608, 1.136]
$HS_1 \rightarrow W_1$	- 0.001 (.006)	-.015	.874	[-0.012, 0.010]
$HS_2 \rightarrow CD_3$	0.199 (.076)**	.335	.009	[0.050, 0.347]
$HS_3 \rightarrow AvSteps_2$	0.264 (.445)	.066	.553	[-0.608, 1.136]
$HS_3 \rightarrow W_2$	- 0.001 (.006)	-.008	.874	[-0.012, 0.010]
$AvSteps_0 \rightarrow CD_1$	- 0.031 (.087)	-.094	.721	[-0.200, 0.139]
$AvSteps_0 \rightarrow HS_1$	- 0.062 (.068)	-.107	.366	[-0.195, 0.072]
$AvSteps_0 \rightarrow W_1$	- 0.004 (.003)	-.113	.234	[-0.010, 0.002]
$AvSteps_1 \rightarrow CD_3$	0.00 (.05)	.003	.995	[-0.098, 0.099]
$AvSteps_1 \rightarrow HS_3$	- 0.062 (.068)	-.882	.366	[-0.195, 0.072]
$AvSteps_1 \rightarrow W_2$	0.013 (.017)	.464	.463	[-0.020, 0.046]
$W_0 \rightarrow CD_1$	1.25 (1.44)	.116	.385	[-1.572, 4.072]
$W_0 \rightarrow AvSteps_1$	- 32.579 (17.732)	-.037	.066	[-67.334, 2.176]
$W_0 \rightarrow HS_1$	- 0.132 (2.722)	-.007	.961	[-5.468, 5.204]
$W_1 \rightarrow CD_3$	- 0.017 (5.298)	-.002	.997	[-10.401, 10.368]
$W_1 \rightarrow AvSteps_2$	-32.804 (41.586)	-.397	.430	[-114.313, 48.705]
$W_1 \rightarrow HS_3$	- 0.796 (5.232)	-.387	.127	[-18.231, 2.280]
M				
CD_{int}	5.550 (.094)**	8.626 (1.134)		[5.365, 5.734]
HS_{int}	2.829 (.112)**	3.542 (1.274)		[2.610, 3.048]

$AvSteps_{int}$	9.023 (.301)**	2.892 (.495)	[8.434, 9.612]
W_{int}	2.040 (.024)**	6.475 (.340)	[1.993, 2.087]
$CD_{linear\ slope}$	0.195 (.063)**	-	[0.071, 0.319]
$HS_{linear\ slope}$	0.702 (.069)**	-	[0.566, 0.837]
$AvSteps_{linear\ slope}$	1.351 (.226)**	-	[0.907, 1.794]
$W_{linear\ slope}$	- 0.040 (.002)**	-	[-0.045, -0.035]
$CD_{quadratic\ slope}$	- 0.021 (.011)	-	[-0.042, 0.001]
$HS_{quadratic\ slope}$	- 0.075 (.010)**	-	[-0.095, -0.055]
$AvSteps_{quadratic\ slope}$	- 0.089 (.019)**	-	[-0.126, -0.053]
$W_{quadratic\ slope}$	0.002 (.00)**	-	[0.002, 0.003]
Fit Statistics			
χ^2	65.249		
df	53		
RMSEA	0.037		
CFI	0.988		

CD = cue detection; HS = habit strength; AvSteps = average physical activity steps; W = weight; CD_{int} = cue detection intercept; HS_{int} = habit strength; $AvSteps_{int}$ = average physical activity steps intercept; W_{int} = weight intercept; $CD_{linear\ slope}$ = cue detection linear slope; $HS_{linear\ slope}$ = habit strength linear slope; $AvSteps_{linear\ slope}$ = average physical activity steps linear slope; $CD_{quadratic\ slope}$ = cue detection quadratic slope; $HS_{quadratic\ slope}$ = habit strength quadratic slope; $AvSteps_{quadratic\ slope}$ = average physical activity steps quadratic slope; $W_{quadratic\ slope}$ = weight quadratic slope; int = latent intercept; linear slope = latent linear growth rate; RMSEA = = root mean square error of approximation; CFI = comparative fit index. * < .05. ** < .01.

Table 4

Eating/Drinking ALT Model Results

Parameter	Unstandardized Coefficient (*SE*)	Standardized Coefficient	*p*	95% CI
Autoregressive Effects				
$CD_0 \rightarrow CD_1$	- 0.118 (.065)	-.204	.070	[-0.246, 0.009]
$CD_1 \rightarrow CD_2$	0.119 (.127)	.122	.347	[-0.129, 0.367]
$CD_2 \rightarrow CD_3$	0.119 (.127)	.115	.347	[-0.129, 0.367]
$HS_0 \rightarrow HS_1$	- 0.152 (.174)	-.150	.383	[-0.494, 0.190]
$HS_1 \rightarrow HS_2$	0.528 (.108)**	.435	.00	[0.317, 0.739]
$HS_2 \rightarrow HS_3$	0.528 (.108)**	.479	.00	[0.317, 0.739]
$AvCal_0 \rightarrow AvCal_1$	- 0.231 (.183)	-.566	.209	[-0.590, 0.129]
$AvCal_1 \rightarrow AvCal_2$	- 1.113 (1.861)	-.391	.550	[-4.760, 2.534]
$W_0 \rightarrow W_1$	0.534 (.348)	.449	.125	[-0.148, 1.215]
$W_1 \rightarrow W_2$	2.520 (1.424)	1.211	.077	[-0.271, 5.312]
Cross-lagged Effects				
$CD_1 \rightarrow HS_1$	- 0.129 (.212)	-.079	.545	[-0.545, 0.288]
$CD_2 \rightarrow HS_2$	0.161 (.152)	.080	.289	[-0.137, 0.460]
$CD_2 \rightarrow AvCal_1$	0.016 (.023)	.087	.487	[-0.030, 0.062]
$CD_2 \rightarrow W_1$	0.000 (.015)	-.003	.975	[-0.030, 0.029]
$CD_3 \rightarrow HS_3$	0.161 (.152)	.075	.289	[-0.137, 0.460]
$CD_3 \rightarrow AvCal_2$	- 0.112 (.091)	-.217	.223	[-0.291, 0.068]
$CD_3 \rightarrow W_2$	0.061 (.033)	.184	.065	[-0.004, 0.126]
$HS_0 \rightarrow CD_1$	0.002 (.104)	.003	.987	[-0.203, 0.206]
$HS_1 \rightarrow CD_2$	0.144 (.052)**	.239	.006	[0.042, 0.246]
$HS_1 \rightarrow AvCal_1$	0.015 (.022)	.130	.515	[-0.029, 0.059]
$HS_1 \rightarrow W_1$	- 0.018 (.008)*	-.179	.027	[-0.034, -0.002]
$HS_2 \rightarrow CD_3$	0.144 (.052)**	.281	.006	[0.042, 0.246]
$HS_3 \rightarrow AvCal_2$	- 0.030 (.038)	-.125	.433	[-0.104, 0.045]
$HS_3 \rightarrow W_2$	- 0.018 (.008)*	-.115	.027	[-0.034, -0.002]
$AvCal_0 \rightarrow CD_1$	0.255 (.482)	.114	.596	[-0.689, 1.199]
$AvCal_0 \rightarrow HS_1$	0.031 (.543)	.009	.954	[-1.032, 1.094]
$AvCal_0 \rightarrow W_1$	0.041 (.082)	.114	.616	[-0.120, 0.202]
$AvCal_1 \rightarrow CD_3$	- 1.164 (1.618)	-.210	.472	[-4.336, 2.007]
$AvCal_1 \rightarrow HS_3$	- 3.750 (3.889)	-.314	.335	[-11.373, 3.873]
$AvCal_1 \rightarrow W_2$	0.948 (1.421)	.513	.505	[-1.837, 3.733]
$W_0 \rightarrow CD_1$	1.335 (1.520)	.181	.380	[-1.644, 4.314]
$W_0 \rightarrow AvCal_1$	- 0.425 (.657)	-.317	.518	[-1.713, 0.863]
$W_0 \rightarrow HS_1$	- 0.727 (2.494)	-.061	.770	[-5.615, 4.160]
$W_1 \rightarrow CD_3$	- 1.075 (1.798)	-.172	.550	[-4.599, 2.448]
$W_1 \rightarrow AvCal_2$	- 2.339 (2.127)	-.729	.272	[-6.507, 1.830]
$W_1 \rightarrow HS_3$	- 4.116 (3.633)	-.306	.257	[-11.236, 3.005]
M				
CD_{int}	5.553 (.067)**	13.118	.00	
HS_{int}	3.115 (.086)**	4.087	.00	
$AvCal_{int}$	1.459 (.028)**	5.665	.00	

W_{int}	2.039 (.024)**	6.515	.00
$CD_{linear\ slope}$	0.308 (.054)**	-	.00
$HS_{linear\ slope}$	0.723 (.057)**	-	.00
$AvCal_{linear\ slope}$	- 0.040 (.003)**	-	.00
$W_{linear\ slope}$	- 0.040 (.003)**	-	.00
$CD_{quadratic\ slope}$	- 0.036 (.009)**	-	.00
$HS_{quadratic\ slope}$	0.723 (.057)**	-	.00
$AvCal_{quadratic\ slope}$	0.003 (.001)**	-	.00
$W_{quadratic\ slope}$	0.002 (.00)**	-	.00
Fit Statistics			
χ^2	52.155		
df	49		
RMSEA	.019		
CFI	.997		

CD = cue detection; HS = habit strength; AvCal = average calorie consumption; W = weight; CD_{int} = cue detection intercept; HS_{int} = habit strength; $AvCal_{int}$ = average calorie consumption intercept; W_{int} = weight intercept; $CD_{linear\ slope}$ = cue detection linear slope; $HS_{linear\ slope}$ = habit strength linear slope; $AvCal_{linear\ slope}$ = average calorie consumption linear slope; $CD_{quadratic\ slope}$ = cue detection quadratic slope; $HS_{quadratic\ slope}$ = habit strength quadratic slope; $AvCal_{quadratic\ slope}$ = average calorie consumption quadratic slope; $W_{quadratic\ slope}$ = weight quadratic slope; int = latent intercept; linear slope = latent linear growth rate; RMSEA = = root mean square error of approximation; CFI = comparative fit index. * < .05. ** < .01.

Table 5

Descriptive statistics: means, standard deviations, and correlations of all variables in the physical activity autoregressive latent trajectory (ALT) model

Physical Activity-Related Measures	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Cue detection (baseline)	-													
2. Cue detection (1.5 months)	.466**	-												
3. Cue detection (2.5 months)	.439**	.568**	-											
4. Cue detection (5 months)	.408**	.487**	.578**	-										
5. Habit Strength (baseline)	.280**	.072	.156	.142	-									
6. Habit Strength (2 months)	.134	.289**	.377**	.256**	.512**	-								
7. Habit Strength	.091	.187	.285**	.239**	.419**	.801**	-							

(3 months)														
8. Habit Strength (6 months)	.108	.050	.244**	.231**	.347**	.618**	.697**	-						
9. Average Steps (baseline)	.053	-.028	-.040	-.073	.169*	.178*	.235**	.203*	-					
10. Average Steps (3 months)	.032	.049	.068	.031	.098	.186	.223**	.171*	.328**	-				
11. Average Steps (12 months)	-.050	.069	-.032	.032	.049	.100	.330**	.247**	.456**	.458**	-			
12. Weight (lbs; baseline)	-.104	-.058	-.126	-.141*	-.145	-.085	-.049	-.017	-.120	-.129	-.187	-		
13. Weight (lbs; 3 months)	-.078	-.061	-.117	-.130	-.097	-.066	-.027	-.087	-.128	-.185	-.220	.973**	-	
14. Weight (lbs; 12 months)	-.088	-.065	-.113	-.130	-.097	-.066	-.027	-.087	-.128	-.190	-.258*	.891**	.945**	-
Sample size	171	148	146	133	171	141	140	126	162	137	81	172	137	108
M	5.535	5.875	5.904	6.015	2.800	4.050	4.233	4.415	9.060	12.440	13.278	2.040	1.924	1.843

SD	1.269	.908	.930	1.007	1.444	1.478	1.530	1.636	3.773	6.150	6.928	.318	.318	.284
Minimum	1.00	2.50	2.00	2.00	1.00	1.00	1.00	1.00	1.278	2.600	4.024	1.433	1.369	.727
Maximum	7.00	7.00	7.00	7.00	7.00	7.00	7.00	7.00	25.605	44.027	49.543	2.976	2.876	.921

Note. *M* and *SD* are used to represent mean and standard deviation, respectively. * indicates $p < .05$. ** indicates $p < .01$. Scores of average physical activity steps have been divided by 1000 and scores of weight has been divided by 100 to facilitate analyses.

Table 6

Descriptive statistics: means, standard deviations, and correlations of all variables in the eating/drinking autoregressive latent trajectory (ALT) model

Eating/Drinking -Related Measures	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1. Cue detection (baseline)	-													
2. Cue detection (1.5 months)	.140	-												
3. Cue detection (2.5 months)	.195*	.558**	-											
4. Cue detection (5 months)	.246*	.506**	.452**	-										
5. Habit Strength (baseline)	.273**	.060	-.059	.089	-									
6. Habit Strength (2 months)	.220*	.084	.224**	.227*	.400**	-								
7. Habit Strength	.280**	.125	-.059**	.373**	.356**	.663**	-							

(3 months)														
8. Habit Strength (6 months)	.286**	.158	.239*	.334**	.368**	.598**	.712**	-						
9. Average Calories (baseline)	-.107	.067	.050	-.050	-.151	-.042	-.098	.018	-					
10. Average Calories (3 months)	-.071	.067	.050	-.050*	-.151	-.042	-.098	.018	.562**	-				
11. Average Calories (12 months)	-.156	-.023	.076	-.182	-.155	-.026	-.075	-.113	.555**	.292**	-			
12. Weight (lbs; baseline)	-.011	.137	.073	-.036	-.071	-.061	-.099	-.029	.419**	.440**	.292**	-		
13. Weight (lbs; 3 months)	-.015	.116	.052	-.064	-.061	-.089	-.149	-.070	-.107**	.067**	.050**	-.050**	-	
14. Weight (lbs; 12 months)	-.071	.117	.075	-.035	-.065	-.102	-.187	-.161	.327**	.372**	.233**	.887**	.941**	-
Sample size	165	143	140	133	171	141	140	126	152	137	92	172	137	108

M	5.510	5.989	6.094	6.205	3.123	4.211	4.613	4.685	1.463	1.364	1.437	2.040	1.924	1.843
SD	.943	.676	.648	.627	1.134	1.062	1.192	1.315	.342	.270	.352	.342	.270	.352
Minimum	2.600	3.800	4.000	4.200	1.000	1.200	1.100	1.000	.404	.682	.876	1.433	1.369	1.280
Maximum	7.000	7.000	7.000	7.000	5.800	6.350	6.850	7.000	2.803	2.438	2.721	2.976	2.876	2.780

Note. M and *SD* are used to represent mean and standard deviation, respectively. * indicates $p < .05$. ** indicates $p < .01$. Scores of average calorie consumption have been divided by 1000 and scores of weight has been divided by 100 to facilitate analys

Appendix A
Supplementary Materials
STEP EQUIVALENTS

As a general rule: 1 minute of moderate intensity exercise = 100 steps
1 minute of high intensity exercise = 200 steps

ACTIVITY	STEP/MIN	ACTIVITY	STEP/MIN
Aerobics-high impact	176	Mowing lawn	137
Aerobics-low impact	132	Racquetball	175
Baseball	62	Rope jumping	250
Basketball	200	Rowing	175
Canoeing	75	Running (high or 16 km/h)	400
Cardio machine (moderate effort)	150	Running (low or 8 km/h)	200
Cardio machine (vigorous effort)	250	Running (med or 13 km/h)	337
Curling	99	Shoveling snow	150
Cycling (fast, vigorous effort)	250	Skateboarding	125
Cycling (leisure moderate effort)	200	Skating-Ice	176
Cycling (leisure, slow, light effort)	150	Skating-Inline	300
Dancing (general)	162	Skiing-Cross Country	200
Field Hockey	200	Skiing-Downhill	150
Football	200	Snowboarding	200
Frisbee	75	Soccer	175
Frisbee-Ultimate	200	Strength training	112
Gardening (general)	100	Swimming laps (moderate)	175
Golfing	112	Swimming laps (vigorous)	250
Gymnastics	100	Table Tennis / Ping Pong	100
Hiking	150	Tennis	150
Hiking-Uphill	175	Track & Field	150
Hockey	200	Trampoline	88
Housework (general)	75	Volleyball	75
Jogging (slow)	175	Water Skiing	150
Karate / Tae Kwan Do / Jujitsu / Judo	250	Walking	88
Kayaking	125	Yoga	62

Preface to Chapter 3

Study 1 provided evidence suggesting that the relationship between habit strength and cue detection later in the intervention are important contributors to the underlying process of behaviour change. What drives cue detection and habit strength to influence behaviour change deserves more investigation. In Study 2, we examined whether if-then plan components are potential BCTs that contribute to our proposed mechanisms of action that lead to eventual behaviour change, namely the psychological variables of cue detection and habit strength. Implementation intentions are behaviour change tools that are frequently used in interventions and shown to be highly effective (Adriaanse, de Ridder, & Wit, 2009; de Vet et al., 2011; Steadman & Quine, 2004). Evidence in the literature indicate that the specificity of implementation intentions plays a critical role in detecting and activating cues, as well as in implementing goal-directed responses in interventions targeting different behaviours and populations (de Vet et al., 2011; Dombrowski, Endevelt, Steinberg, & Benyamini, 2016; Fleig et al., 2017; van Osch, Lechner, Reubsaet, & De Vries, 2010). Thus, I sought to examine the relationship between specificity in implementation intentions, cue detection, and habit strength. Precisely, I examined the separate relationships between the specificity of the "if" component of implementation intentions (cue specificity) and cue detection, as well as between the "then" component (response specificity) and habit strength using an autoregressive latent trajectory model with structured residuals (ALT model). We hypothesized that higher levels of cue specificity are associated with higher levels of cue detection, and reciprocally, greater cue detection in turn is related to subsequent greater cue specificity for both the physical activity and eating/drinking behaviours data (Hypothesis 1). We also hypothesized that greater response specificity is associated with greater habit strength, and reciprocally, greater habit strength in turn relates to subsequent greater response specificity for both the physical activity and eating/drinking behaviours data (Hypothesis 2).

Chapter 3: Greater Response Specificity in Implementation Intentions (If-Then Plans) is Related to Greater Healthy Habit Strength

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Abstract

Behaviour change is challenging to achieve and even more difficult to maintain over the long term. The present study examines the influence of the specificity of the cue (if-component) and response (then-component) in implementation intentions on cue detection and habit strength for healthy eating/drinking. Content analysis of if-then plans formed by participants (*N* = 83) in the initial 6-month observation period of a 12-month lifestyle modification intervention was conducted. The specificity of the if-component (cue) and then-component (response) of implementation intentions was coded as either high or low specificity. Aggregated specificity scores at four time points were calculated for both cue and response plan components. Cue detection and habit strength measured at five time points including baseline were used in data analyses. Within-person cross-lagged effects between cue specificity and cue detection, as well as between response specificity and habit strength were examined in two eating-related and two physical activity-related models. Between-person change in each of these variables over the course of treatment was also examined. Results showed that higher levels of response specificity in eating/drinking-related if-then plans were associated with higher levels of eating/drinking habit strength at later time points. Greater eating/drinking cue detection was related to subsequent greater cue specificity in eating/drinking-related if-then plans. Higher levels of physical activity habit strength were related to subsequent lower levels of response specificity in physical activity-related if-then plans at most time points. Our findings highlight the important roles of individual components of implementation intentions on cue detection and habit strength and vice versa.

Keywords: behaviour change, specificity, implementation intentions (if-then plans), cue detection, habit strength

Introduction

Unhealthy lifestyle behaviours contribute to a variety of chronic diseases, and abundant research has been dedicated to altering behaviours. However, behaviour change is difficult to achieve and even more difficult to sustain over the long term (Bouton, 2014). To address this issue, researchers have examined potential psychological predictors that facilitate behaviour change and maintenance, including behavioural automaticity in response to situational cues and the cue-response link reinforced by implementation intentions (Gardner, 2012; Gollwitzer & Sheeran, 2006).

Implementation intentions (if-then plans) are one of the most commonly used techniques in habit formation interventions. They are concrete action plans that specify, in an if-then format, when, where, and how one will act in order to achieve a specific goal ("If situation Y occurs, then I will initiate goal-directed behaviour X!" (Gollwitzer, 1993, 1999). These plans allow individuals to successfully reach their goals despite problems that may arise, such as competing goals, temptations, and previously formed poor habits (Gollwitzer, 1999). Forming if-then plans has been found to be much more effective than relying solely on motivation and willpower, as expressed in mere goal intentions ("I will do X"). A large meta-analysis found medium-to-large effects of if-then plans on goal achievement across many behaviour domains (94 studies, d = .65) (Adriaanse, de Ridder, & Evers, 2011; Gollwitzer & Sheeran, 2006). By forming them, a mental representation of the "cue" situation becomes highly activated, allowing for easy detection, recall, as well as immediate and efficient responding, without exerting conscious and cognitive effort (Gallo & Gollwitzer, 2007; Gollwitzer & Schaal, 1998). Thus, the individual can switch from exercising their conscious and goal-directed behaviours to being automatically controlled by the selected situational cues (e.g. reaching for an apple instead of a bag of chips when watching television becomes a habit) (Gallo & Gollwitzer, 2007; Gollwitzer & Schaal, 1998).

Numerous studies have shown that increasing the activation of situational cues (if-process) and automating the goal-directed cognitive or behavioural response to that cue (then-process) using implementation intentions can facilitate goal striving (Bayer, Achtziger, Gollwitzer, & Moskowitz, 2009; Gollwitzer, 1999; Parks–Stamm, Gollwitzer, & Oettingen, 2007; Webb & Sheeran, 2007). Evidently, both the if- and then-components as well as the cue-response linkage play critical roles in behaviour change.

Specificity of Implementation Intentions

To understanding how implementation intentions influence the processes that lead to behaviour change, it is imperative to examine the role of specificity of implementation intentions in this process. The influence of specificity of implementation intentions has been examined in various health contexts, including interventions for smoking cessation, condom purchase and use, physical activity in different populations, and weight loss (de Vet et al., 2011; de Vet, Oenema, & Brug, 2011; Dombrowski, Endevelt, Steinberg, & Benyamini, 2016; Fleig et al., 2017; van Osch, Lechner, Reubsaet, & De Vries, 2010; Verbiest et al., 2014; Ziegelmann, Lippke, & Schwarzer, 2006). The specificity of if-then plans has been shown to play a critical role in detecting and activating cues, as well as in implementing goal-directed responses.

For example, in a study on ceasing smoking habits using implementation intentions, Osch and colleagues (2010) showed that providing greater details increases the efficacy of if-then plans for smoking cessation. Verbiest and colleagues (2014) obtained similar results in their study, in that greater specificity of if-then plans predicted higher smoking abstinence rates. In the context of sexual health and condom purchase/use, de Vet and collegues (de Vet et al., 2011) found that when participants made more precise plans on preparatory or target behaviours concerning buying, using, discussing condoms, the more likely they were to complete the target behaviours. In the physical activity behaviours context, several studies have examined the role of specificity of implementation intentions on plan enactment and subsequent behaviour change in both community samples and clinical samples (e.g., patients in orthopedic or cardiac rehabilitation). A study by de Vet and colleagues (de Vet et al., 2011) showed that those who formed more specific implementation intentions were more physically active two weeks later in contrast to their baseline measurements of physical activity. Fleig and colleagues (Fleig et al., 2017) found through a behavioural intervention in cardiac and orthopaedic rehabilitation that specificity of occasion cues (i.e., when to act) and highly instrumental plans were positively associated with plan enactment. Finally, Ziegelmann and colleagues (Ziegelmann, Lippke, & Schwarzer, 2006) showed that the orthopaedic rehabilitation patients who were assisted by their group coach formed more specific and more complete action plans, and also performed more physical activity over a longer period of time up to six months after discharge than those who created plans on their own. In the weight loss domain, Dombrowski and colleagues (Dombrowski, Endevelt, Steinberg, & Benyamini, 2016) found that greater food-related if-then plan specificity predicted greater weight loss in participants, particularly in participants who had more ambitious weight loss goals. In summary, highly specific if-then plans have been shown to be much more effective than non-specific plans in enforcing various health behaviour changes.

Overall, the consensus in the literature is that the greater the specificity of the if-then plans, particularly that of the cues in the if-component of the plan, the greater the likelihood that the plan will be enacted and the target behaviour(s) will be achieved. To our knowledge, we are the first to examine the effect of separate plan component specificity on intermediary changes in psychological factors rather than the resulting behaviour itself, i.e. we are the first to study the effect of specificity of cues and actions in the if-then plans on cue detection and habit strength. Examining the distinct effects of cue (the “if” component) and response (the “then” component) specificity on cue detection and habit strength can help us better understand the mechanisms that lead to behaviour change. We are also the first to examine the effects of if-then plans’ cue and response components in the context of a longitudinal lifestyle intervention.

Past studies have mostly focused on identifying, detecting, or monitoring different types of cues in the “if” component of the implementation intentions, response initiation in the “then” component, and the cue-response link (Adriaanse, de Ridder, & Wit, 2009; Bayer, Achtziger, Gollwitzer, & Moskowitz, 2009; Parks–Stamm, Gollwitzer, & Oettingen, 2007; Verhoeven, Adriaanse, de Vet, Fennis, & de Ridder, 2014). However, the studies are usually much shorter in duration (e.g., one-time intervention in lab settings or a week to several weeks in ongoing life) than the 12-month-long intervention of the present study [of which we are analyzing the first six months, as explained below]. With a longer observation period, we can examine whether higher cue and response specificity in implementation intentions increase cue detection and habit strength, and whether the relationship of greater cue detection and habit strength also predict higher cue and response specificity, respectively, over time. Moreover, some studies provide fixed templates of if-then plans for their participants (i.e. they provide a few pre-determined options of cues and potential action responses for participants to choose from). In contrast, we meticulously coached participants one-on-one at each session without using a fixed template, and we encouraged them to select their own cues and helped them determine how they would respond. For instance, one participant’s self-selected “problematic” behaviour may be about reducing alcohol consumption, whereas another participant may have chosen to create if-then plans to manage their consumption of sugary foods or increase spontaneous physical activity. There was no limit in the number of if-then plans and the number of health behaviours participants could choose. The plans were entirely personalized, and participants could change them from session to session. Therefore, having a high degree of freedom in choosing their own cues and action responses is more representative of real-life situations than only being able to choose from a limited number of options. This has the potential of being more effective.

Furthermore, the coaches followed up with their participants through phone or email between sessions or during the subsequent session to help them continue to refine their plans until the plans were implemented successfully and eventually became habits. With one-on-one guidance of a coach throughout the 6-month-long observation period, participants learned to create if-then plans tailored to manage their self-selected "problematic" health behaviours based on the content of each session, as well as how to revise their plans if their chosen cues and responses did not work for them.

In summary, the present study examines the effects of individual components of implementation intentions, namely the effects of specificity of the if-component cue and then-component action response on cue detection and habit strength, respectively. To date, this is the first study that examines the effects of cue and response specificity of implementation intentions on psychological variables instead of directly on behaviour change, which can enhance our understanding of the mechanisms behind behaviour change. By having participants create personalized if-then plans, having a year-long intervention, and the 6-month-long duration of the observation period, the present study better represents cue and response situations encountered in everyday life over time.

Method

Data collection took place from 2013 to 2017. For this study, we examined the effects of cue and response specificity on cue detection and habit strength in physical activity and eating/drinking behaviours-related if-then plans, respectively. These if-then plans were collected from participants in the experimental condition of a two-arm randomized controlled trial, namely a lifestyle behaviour change intervention with changes in body weight as the primary outcome (Knäuper et al., 2014). Empty copies of if-then plan summary sheets were provided for participants at every session for them to create new plans or revise existing plans. They were given a folder at the first session to keep all their summary sheets in. Participants were guided by their group coach to create if-then plans at the end of every session, and then asked to bring the folder home to apply the if-then plans in their daily life for the time between sessions. At the beginning of the subsequent session, they were asked to bring the folder back and revise any if-then plans that did not work or remove any plans that have already become habits. For participants who were absent at specific sessions, their coaches followed up with the revision process through email or over the phone between sessions. This revision process continued throughout the entire year-long intervention.

Participants

Study participants were recruited from the community using flyers and email announcements (e.g., at local YMCAs). Individuals with overweight or obesity (BMI of 28-45, waist circumference ≥ 88 cm for women, ≥ 102 cm for men, 18-75 years of age) were eligible if they engaged in fewer than 200 minutes of self-reported moderate or vigorous physical activity per week. Exclusion criteria included any limitation that would preclude full participation in the intervention or could have a confounding effect on the primary outcomes, including having been diagnosed with diabetes, taking metformin, and planning to become pregnant. The published study protocol includes the full list of screening exclusion criteria (Knäuper et al., 2014).

A total of 864 individuals completed the initial screening and 208 were randomized, out of which 172 participants received the year-long weight loss intervention. A detailed flowchart of the study design, including randomization was presented in the published trial protocol (Knäuper et al., 2014) and results of the randomized controlled trial (Knäuper et al., 2018). The present study examines data collected from participants in only the experimental condition, of which 83 individuals created eating/drinking-related if-then plans and 81 individuals made physical activity-related if-then plans. Therefore, $N = 83$ is the sample size for the eating/drinking behaviours models and $N = 81$ for the physical activity models. Participants in the control condition did not create if-then plans, and thus their data are not used in this study. Because the sample sizes are very similar between the physical activity and eating/drinking behaviours data, demographics information presented in Table 1 is based on the sample of participants who created eating/drinking-related if-then plans.

Measures

Cue Detection

Cue Detection for Lack of Physical Activity. Cue detection for lack of physical activity was assessed with two questions developed for the purpose of the present study ("I notice when I sit for too long" and "I notice what keeps me from exercising [e.g., weather, fatigue, busy schedule, lack of motivation]"). The correlation of these two questions was $r = .37$, $p < .001$ at baseline and $r = .41$, $p < .001$ at 2.5 months. For every question, participants were asked to rate the degree to which they notice these cues on a 7-point Likert-type rating scale that ranged from 1 (disagree) to 7 (agree).

Eating/Drinking Cue Detection. The eating/drinking cue detection was measured with five questions, developed for the purpose of the present study (1) “I notice when I am doing something else while I am eating. (e.g., watching TV, using the internet).” (2) “While I am eating or drinking, I notice what and how much I consume”, (3) “I notice how much food I put on my plate”, (4) “I notice when there is junk food in my house”, and (5) “I noticed when I am stressed or feeling down”. The internal consistency was $\alpha = .70$ at baseline and $\alpha = .61$ at 2.5 months.

Habit Strength

Using the 4-item Self-Report Behavioural Automaticity Index (SRBAI) (Gardner, 2012; Gardner, Abraham, Lally, & Bruijn, 2012), seven behaviours were examined in this questionnaire to measure habit strength. The two physical activity behaviours and five eating/drinking behaviours on the SRBAI correspond to the two physical activity cues and five eating/drinking cues on the cue detection questionnaire, respectively. The SRBAI is a short version of the 12-item Self-Report Habit Index (SRHI) (Verplanken & Orbell, 2003) that retains only the four items that assess automaticity. These items are “I do automatically”, “I do without having to consciously remember”, “I do without thinking”, and “I start doing before I realize I’m doing it”. A Likert-type rating scale ranging from 1 (disagree) to 7 (agree) was provided to rate each of the 12 behaviours.

Physical Activity Habit Strength. Two physical activity behaviours were used to analyze change in physical activity habit strength: “spending more time moving instead of sitting’’ and “exercising for at least 150 minutes per week”. The correlation between these two behaviours was $r = .54$, $p < .001$ at baseline and $r = .59$, $p < .001$ at 3 months. The mean score was calculated by averaging the scores of the four automaticity items of these two behaviours at baseline and at the 3-month time point, respectively.

Eating/Drinking Habit Strength. Change in eating/drinking habit strength was assessed for five behaviours on the SRBAI related to eating/drinking. Internal consistency $\alpha = .67$ at baseline and $\alpha = .79$ at 3 months. Eating/drinking habit strength mean scores were computed using the same method as for physical activity habit strength scores.

If-Then Plan Specificity

Participants in the experimental condition were trained to create individualized if-then plans throughout the 22 sessions during the 12-month-long intervention, during which if-then plans from the initial 6 months were used in the present study. The initial 3-month intensive teaching period of the intervention consisted of 12 weekly sessions, followed by a month of 2 bi-weekly sessions, and eventual monthly sessions until the end of the intervention.

Only if-then plans from the initial 6 months were analyzed because we expected greater changes in habit strength and cue detection to occur when sessions were more frequent and closer together in time. Sessions during the first 6 months ranged from weekly, bi-weekly, to monthly frequencies. After the 6-month time point, the subsequent time point is at 11 months for cue detection and 12 months for habit strength. Therefore, we excluded if-then plans created or remaining from the 11-month and 12-month time points because the time span of 5 to 6 months between these two time points was much longer than the initial weekly, bi-weekly, and monthly frequencies, which may skew the analyses results.

The plans were classified into categories of physical activity, eating/drinking behaviours, weighing, online tracking of physical activity and food consumption, and miscellaneous if-then plans. The majority of if-then plans created were related to eating/drinking behaviours or physical activity, and thus the present study is focused on analyses of if-then plans from these two categories. The content of if-then plans varied greatly across participants. For example, one participant could have created various if-then plans to target their sedentary behaviours and becoming more physically active, while another could have many if-then plans to target the reduction of their high sugar intake. All if-then plans were analyzed in a ‘carried forward’ database, meaning that the if-then plans created in a previous session that were still used by participants got carried forward into the subsequent session. Plans were only removed if they were no longer used or needed by participants.

The specificity of 14089 eating/drinking behaviours-related plans and 9250 physical activity-related plans was rated in the carried forward database based on a dichotomous coding scheme that we developed (Appendix B), in which cues (the “if” component) and responses (the “then” component) were coded separately. The coding scheme features a two-point coding system in which the cue and the response was rated either one or two points, with one point assigned for low specificity and two points for high specificity. “If” or “then” components of the plan were rated as highly specific if they provided precise details of what, who, and how the plan would be carried out (and when or where depending on if the time or location was necessary to specify). For example, “If I am craving chocolate, then I will have an apple instead” contained a highly specific cue and response in the “if” and “then” components, respectively. In contrast, low specificity refers to vague if-then plan components that did not provide enough information on what, who, and how the plan would be enacted (and when or where depending on whether these two details were important in the plan). For example, “If I want to increase my exercise, then I will try new types of exercise to stimulate me more” contains a vague cue and response. Neither concrete cues to exercise in the “if” component nor specific types of exercise in the “then” component were provided. Further concrete details are needed in this if-then plan.

Two coders independently rated physical-activity related if-then plans and another two coders independently rated the eating/drinking behaviours-related if-then plans. The same coding scheme was used for both physical activity and eating/drinking behaviours-related plans in this study. On average, each participant made 169.75 eating/drinking-related if-then plans and 114.20 physical activity-related if-then plans during the entire intervention, which was calculated from the carried forward database. The average number of eating/drinking-related plans created per session ranged from 1.74 to 12.40, with the first session being the smallest average number of plans and the final session being the largest number. The quantity of plans made increased steadily throughout the intervention. Additionally, the average number of physical activity-related plans ranged from 1.09 to 7.72. The first session also had the smallest number of plans, which steadily increased until the final session, which had the greater number of plans.

To ensure inter-coder reliability and standardization of coding, two raters (the first author and an undergraduate research assistant) independently rated seven rounds of 20 and five rounds of 50 randomly selected eating/drinking-related if-then plans from the database, which helped fine-tune the coding instructions. After every round of rating, we discussed and resolved discrepancies. Inter-rater reliability ranged from 77.5% to 97.5% for the dichotomous coding (high versus low specificity). Although the range of reliability fluctuated from one round to the next, we improved overall and reached 95% in the final round. Inter-rater reliability was calculated using percentage of agreement. Due to the flexibility of our if-then plans, we concluded that after 12 rounds of rating randomly selected plans in the database and achieving consistently high reliability in later coding rounds, we were ready to rate the remaining if-then plans. We discussed and resolved discrepancies after each set of 100 plans as we coded the remaining plans.

All physical activity and eating/drinking-related if-then plans' cue and response components were coded, and thus there were no missing data in the individual if-then plan cues and responses. However, due to some participants not creating if-then plans during certain sessions, the aggregated scores of the cue and response components cannot be computed, and thus will result in missing data. In the physical activity behaviours-related data (including physical activity cue detection, habit strength, average physical activity steps, and weight), 35.80% of individuals had complete data, while 6.1% had missing data in one variable, and the remaining individuals had missing data in two or more variables. In the eating/drinking behaviours-related data, 46.99% of participants had complete data, while 16.87% had missing data in one variable, and the remaining participants had missing data in two or more variables. These percentages refer to the percentage of participants having complete data in all four variables in the models (i.e., cue detection, habit strength, behaviour change – physical activity steps in the physical activity model and average calorie consumption in the eating/drinking model, and weight) at all time points included in the analyses. The quantity of complete data decreased over time due to a combination of potential reasons, including participants forgetting to complete some questionnaires despite reminders and dropouts at later sessions in the intervention.

Cue Specificity/Response Specificity Aggregated Scores Computation and Cue Detection/Habit Strength Questionnaire Administration Timeline

Physical Activity and Eating/Drinking Cue Specificity

For the present analyses, aggregated scores for physical activity cue specificity were computed at four time points. Physical activity cue specificity scores from session 2 represented cue specificity at time 1. Scores from session 1 were excluded because 31 individuals did not create any eating/drinking-related if-then plans and 71 individuals did not create any physical activity-related if-then plans in the first session yet. Aggregated scores calculated between sessions 3 to 6 represented cue specificity at time 2. Subsequently, aggregated scores calculated from sessions 7 to 10 represented cue specificity at time 3. Finally, aggregated cue specificity scores calculated from sessions 11 to 15 represented cue specificity at time 4. Eating/drinking cue specificity aggregated scores were computed in the same way. Refer to Figure 2 for details.

Physical Activity and Eating/Drinking Response Specificity

Aggregated scores for physical activity response specificity were computed at four time points. Aggregated physical activity response specificity scores calculated from sessions 2 to 4 represented response specificity at time 1. Subsequently, aggregated scores calculated from sessions 5 to 8 represented response specificity at time 2. Aggregated scores calculated from sessions 9 to 12 represented response specificity at time 3. Finally, aggregated scores calculated from sessions 13 to 16 represented response specificity at time 4. Eating/drinking response specificity aggregated scores were computed. Aggregated scores of cue and response specificity computation with specific session numbers can be found in Figure 2. The session specificity scores that we selected to calculate the average scores corresponded to the lagged measurement time points of cue detection and habit strength. Therefore, not the same sessions were used to calculate cue specificity and response specificity.

Cue Detection and Habit Strength Questionnaire Administration Timeline

We administered both the cue detection and habit strength questionnaires at baseline, represented by cue detection and habit strength at time 0, respectively. Cue detection was afterwards assessed at 0.5, 1.5, 2.5, 5, and 11 months, which are represented by cue detection times 1 to 4, respectively. Habit strength was assessed again at 1, 2, 3, 6, and 12 months, which are represented by habit strength times 1 to 4, respectively. Further details of questionnaire administration time points are available in Xu et al. (in preparation) and in Figure 1 of this study. In the present study, we used almost all the data collected on cue detection and habit strength, except data from the final two time points, namely the 11-month data of cue detection (time 4) and the 12-month data of habit strength (time 4). We focused on the first 6 months of the intervention given the frequency of the measurement during this period. Specifically, to examine change in a given variable, the interval time between assessment points and the number of assessment points must be proportional to the expected rate of change in the variable (Ebner-Priemer & Trull, 2012). Evidence suggests that individuals who exercised at a gym can develop activity habits in the first five weeks (Armitage, 2005) and that it takes 18 to 254 days, with an average time of 66 days to form eating, drinking, and physical activity habits (Lally, Van Jaarsveld, Potts, & Wardle, 2010). Therefore, we examined change in habit strength and cue detection by utilizing the measurements obtained in the first 6 months of the study. During this period, the time intervals between measurement points in the first six months of intervention varied from 0.5 to 2.5 months for cue detection, and one to three months for habit strength. In contrast, during the last six months of the intervention, the time interval between measurement points was six months both for cue detection and habit strength. Details of questionnaire administration time points can be found in Figure 1.

Hypotheses

We hypothesized that higher levels of cue specificity are associated with higher levels of cue detection, and reciprocally, greater cue detection in turn is related to subsequent greater cue specificity for both the physical activity and eating/drinking behaviours data (Hypothesis 1). We also hypothesized that greater response specificity is associated with greater habit strength, and reciprocally, greater habit strength in turn relates to subsequent greater response specificity for both the physical activity and eating/drinking behaviours data (Hypothesis 2).

Analytic Strategy

We used the autoregressive latent trajectory model with structured residuals (ALT model) (Bollen & Curran, 2004; Curran & Bollen, 2001; Curran, Howard, Bainter, Lane, & McGinley, 2014) to examine how cue and response specificity, cue detection, and habit strength individually and jointly unfold over time. The ALT model combines latent curve modeling that focuses on the growth process of variables over time with time series analysis that examines time-specific components of change. Importantly, the ALT model allows for a disaggregation of the between-person (person-specific) differences in change over time from within-person (time-specific) processes of change. Between-person differences represent how the stability and change in the variable of interest over time vary between individuals, whereas within-person differences measure how the variable remains stable or changes within an individual over time (i.e., comparing the same measure at two different time points of the same individual). Furthermore, using multivariate ALT, it is possible to model how between-person and within-person change processes covary over time. Specifically, in the present study, we are interested in examining the bidirectional relationships between cue specificity and cue detection, as well as that between response specificity and habit strength, at both the between-person and within-person levels.

Model building proceeded as following. First, the parameters of (i.e., intercepts, linear slopes, quadratic slopes) latent growth curves were estimated using the observed repeated measures of cue specificity, cue detection, response specificity, and habit strength, respectively. The variances of these growth curve parameters were set to be random (i.e., varying across individuals) and covariances among them were estimated. The variances of the growth curve parameters indicate the extent to which individuals among each other in initial starting point and the rate of change in each variable. The covariances indicate the extent to which these growth curve parameters covary within individuals (e.g., an individual's initial starting point – intercept – is related to the individual's linear rate of change). When found to be not statistically different from zero, the variances of these growth parameters were fixed to 0.

The residuals, which represent the deviations of the observed repeated measures from the expected score given the underlying growth curve trajectory, were modeled as follows. Autoregressive paths were added between pairs of successive residuals (e.g., the residual of cue detection at 2.5 months was regressed on the residual of cue detection at 5 months). These autoregressive paths represent relationships between pairs of successive residuals unaccounted for by the underlying growth trajectory.

Next, cross-lagged regression paths between pairs of successive residuals were added. In Models 1 and 3, the residuals of physical activity (Model 1) and eating/drinking (Model 3) cue detection at time 1 to 4 were regressed on the residuals of physical activity/eating and drinking cue specificity at time 1 to 4, respectively. Simultaneously, paths from cue specificity at time 1 to 4 regressed on cue detection residuals at time 0 to 3 to the residuals, respectively, were added (see Figure 3). In Models 2 and 4, the residuals of physical activity (Model 2) and eating/drinking (Model 4) habit strength at time 1 to 4 were regressed on the residuals of physical activity/eating and drinking response specificity at times 1 to 4, respectively. At the same time, physical activity and eating/drinking response specificity residuals from time 1 to 4 were regressed on physical activity and eating/drinking habit strength from time 0 to 3, respectively (see Figure 4). The estimates of these cross-lagged regression paths represent prospective influences of one variable on the other variable within an individual. For example, higher-than-average eating/drinking response specificity at time 2 is associated with a higher-than-average eating/drinking habit strength at time 2.

All analyses were conducted using Mplus 8.3 (Muthén, Muthén, & Asparouhov, 2017). Missing data were handled with the full information maximum likelihood (FIML) estimation method with robust standard errors, which allows all data (i.e., the complete sample of participants in the experimental condition) to be included in the estimation (Enders & Bandalos, 2001; Graham, 2009). Missing data were imputed internally in the same model, with data collected at other time points predicting the missing data. The FIML method produces unbiased estimates under the assumption that data is missing completely at random (MCAR; Graham, 2009; Muthén et al., 2016). As Little's missing completely at random test was not significant (p = .448 for the variables in the eating/drinking behaviours models and p = .231 for the variables physical activity models), the pattern of missing data is assumed to follow an MCAR pattern.

Differences in autoregressive regression path estimates across time points were examined by comparing the fit of a model in which the path estimates were permitted to differ across time points with the fit of a model in which the estimates were restricted to be equal across these time points. Model comparison was conducted using the rescaled -2 log likelihood difference test, which is distributed as chi-squared with degrees of freedom equal to the rescaled difference in the number of parameters between models (Satorra & Bentler, 2010). An α-value of .05 was used to determine whether these path estimates differed across time points. Pooled estimates are subsequently reported when no difference across time points in these autoregressive path estimates was found. The same strategy was used to examine differences across time points in the cross-lagged path estimates.

The fit of the final model was evaluated with the following fit indices: chi-square value, the Comparative Fit Index (CFI > .90 are satisfactory values), and the Root Mean Square Error of Approximation (RMSEA < .08 are satisfactory values), Tucker Luis Index (TLI > .90), and Standardized Root Mean Square Residual (SRMR < .08 are satisfactory values) (Hooper, Coughlan, & Mullen, 2008; Hu & Bentler, 1999; MacCallum, Browne, & Sugawara, 1996; Steiger, 2007; West, Taylor, & Wu, 2012).

Results

Model 1: Physical Activity Cue Specificity Predicting Cue Detection Model

The fit of model 1 was satisfactory, as shown in model fit statistics indicated in Table 2. At the between-person level, a linear increase in cue detection was found (also see "*M*" scores at the bottom of Table 2). Physical activity cue detection increased over time such that on average participants reported an increase in the detection of physical activity cues over the initial 6-month observation period.

At the within-person level, the estimates of the autoregressive paths from cue specificity at a previous time point to cue specificity at the subsequent time point were positive and significant between all four time points (see "autoregressive effects" in Table 2). Higher levels of cue specificity at a previous time point were associated with higher levels of cue specificity at the subsequent time point. No statistical difference in the size of these estimates was found across all time points. The estimates of the autoregressive paths from physical activity cue detection at a previous time point to cue detection at time the subsequent time point were not significant across all time points.

The cross-lagged path estimates of physical activity cue detection regressed on physical activity cue specificity were not significant across all time points (see "cross-lagged effects" in

Table 2). Similarly, the cross-lagged paths of physical activity cue specificity regressed on cue detection were also not significant.

Model 2: Physical Activity Response Specificity Predicting Habit Strength Model

Model 2 showed satisfactory model fit, as indicated by model fit statistics reported in Table 3. At the between-person level, habit strength increased over the treatment period as indicated by a positive linear slope. However, a significant negative quadratic effect suggested that the rate of increase in habit strength decelerated over the measurement period. Response specificity decreased over time as shown by a negative linear slope (see "*M*" scores in Table 3).

At the within-person level, the autoregressive paths of physical activity response specificity at a previous time point to physical activity response specificity at the subsequent time point were significant between all four time points (see "autoregressive effects" in Table 3). The autoregressive path estimates were not statistically different from one another between time 1 to 3; the estimate was larger between time 3 and 4. Higher levels of response specificity at a previous time point were associated with higher levels of response specificity at a subsequent time point. Physical activity habit strength at a previous time point was positively associated with the subsequent habit strength as indicated by significant autoregressive path estimates. The estimates between time 0 to 2, as well as between time 3 to 4 were not statistically different from each other; this path estimate was larger between time 2 and 3.

The cross-lagged estimates of physical activity habit strength at time 1 to 3 regressed on physical activity response specificity at time 1 to 3 were not significant (see "cross-lagged effects" in Table 3). However, cross-lagged path of physical activity habit strength at time 4 regressed on response specificity at time 4 was significant: higher levels of physical activity response specificity at time 4 were associated with lower levels of habit strength at time 4. The cross-lagged paths from habit strength at time 0 to 2 to physical activity response specificity at time 1 to 3 were significant, respectively. These path estimates were not statistically different from each other. Higher levels of physical activity habit strength at a previous time were associated with lower levels of specificity of the response component of the physical-activity related if-then plans at the subsequent time point. The cross-lagged path from habit strength at time 3 to response specificity at time point 4 was not significant.

Model 3: Eating/Drinking Cue Specificity Predicting Cue Detection Model

Model 3 showed satisfactory model fit, as shown in Table 4 fit statistics. At the between-person level, we found that eating/drinking cue detection increased linearly as shown by a positive linear slope, with the rate of increase decelerating over the treatment period as indicated by a negative quadratic slope (see "*M*" scores in Table 4 for more details).

At the within-person level, the autoregressive paths of eating/drinking cue specificity were positive and significant between all four time points (see "autoregressive effects" in Table 4). No statistical difference among these estimates was found. Higher levels of eating/drinking cue specificity at the previous time point were associated with higher levels of eating/drinking cue specificity at the subsequent time point. The autoregressive paths of eating/drinking cue detection were not significant between all four time points.

Estimates of cross-lagged paths from eating/drinking cue specificity to eating/drinking cue detection were not significant between all the time points (see "cross-lagged effects" in Table 4). The cross-lagged paths from eating/drinking cue detection at time 0, 2, and 3 to eating/drinking cue specificity at time 1, 3, and 4, respectively, were marginally significant suggesting that higher levels eating/drinking cue detection were associated with cue specificity.

The cross-lagged path from eating/drinking cue detection at time 1 to eating/drinking cue specificity at time 2 was not significant.

Model 4: Eating/Drinking Response Specificity Predicting Habit Strength Model

Model 4 also showed satisfactory model fit, as displayed in Table 5. At the between-person level in this model, we found that eating/drinking habit strength increased linearly as indicated by a positive linear slope. The rate of linear increase of eating/drinking habit strength decreased over the treatment period as shown by a negative quadratic slope, (see "*M*" scores in Table 5). Eating/drinking response specificity decreased linearly as shown by a negative linear slope.

At the within-person level, a few autoregressive paths between two successive measurements of eating/drinking response specificity were significant. Namely, eating/drinking response specificity at time 1 and 2 was positively associated with response specificity at time 2 and 3, respectively. No difference in these paths was found. For habit strength, the autoregressive paths from eating/drinking habit strength at time 1 to 3 to habit strength at time 2 to 4, respectively, were significant. No statistical difference among these estimates was found. The estimate of the autoregressive path from time 0 to 1 was not significant. Refer to Table 5 for more details.

The cross-lagged paths from eating/drinking response specificity at time 2 to 4 to eating/drinking habit strength at time 2 to 4, respectively, were significant. Greater response specificity in eating/drinking-related if-then plans was associated with greater eating/drinking habit strength at these time points (refer to "cross-lagged effects" in Table 5). The path from eating/drinking response specificity at time 1 to eating/drinking habit strength at time 1 was not significant. The cross-lagged paths of eating/drinking response specificity regressed on eating/drinking habit strength were not significant at all the time points (see Table 5 for further details). Tables 6 to 9 display the descriptive statistics and correlations for the variables used in Model 1 to 4, respectively.

Discussion

The present study is the first to examine the separate effects of the if- and then-components on intermediary changes in cue detection and habit strength, respectively, instead of directly examining resulting behavioural outcomes. Consistent with expectations, physical activity cue detection increased linearly over the 6-month observation period for all participants. However, no change was found in physical activity cue specificity. Physical activity habit strength also increased linearly across all participants during the 6-month observation period, although the increase deccelerated overtime. Contrary to what was predicted, physical activity response specificity decreased over time across participants. Eating/drinking cue detection increased over time, although its increase deccelerated over the observation period. Similar to physical activity cue specificity, no change was found in eating/drinking cue specificity. Lastly, eating/drinking habit strength increased and its increase deccelated over time. Eating/drinking response specificity also decreased over time, contrary to our expectations.

Hypotheses 1 and 2 on the cross-lagged relationships in the four models were partially supported. Namely, in the cross-lagged effects of the physical activity-related data, higher than average physical activity habit strength in the first two months was associated with lower than average physical activity response specificity in the first three months. Higher than average physical activity response specificity was associated with lower physical activity habit strength at 6 months. Furthermore, higher levels of eating/drinking cue detection at baseline and between 1.5 to 2.5 months were associated with higher levels of cue specificity at 0.5 month and between

1.5 to 5 months. Finally, higher levels of eating/drinking response specificity between 1 to 6 months were associated with higher eating/drinking habit strength between 2 to 6 months. The findings suggest that specificity of the if- and then-components in the eating/drinking-related if-then plans are closely associated with eating/drinking cue detection and habit strength, respectively, whereas only physical activity response specificity is associated physical activity habit strength.

Despite the lack of association between physical activity cue specificity and cue detection, greater physical activity habit strength was associated with lower subsequent response specificity at most time points. This implies that as physical activity habit strength strengthens over time, the importance of response specificity reduces as the target physical activity behaviour becomes more automatic and thus the habit becomes stronger.

In contrast, the relationship between eating/drinking cue detection and cue specificity was significant at most time points, in that greater cue detection was associated with greater subsequent cue specificity. A potential reason for this difference could be that physical activity cues and eating/drinking cues vary greatly. Physical activity cues could be simpler, more consistent, and lower in quantity than eating/drinking cues in everyday life. For example, physical activity cues could be visual cues such as placing one's gym bag or running shoes beside the door or an auditory reminder on one's cell phone to go for a walk, and participants were encouraged to use the same cues regularly. Therefore, individuals may not need to refine their cues in their if-then plans to be more specific over time if they are consistently using the same cues. Moreover, people also do not need to deploy additional cognitive resources to detect these cues if they are the same ones used regularly. As a result, physical activity cue specificity and cue detection do not have a signficant cross-lagged relationship.

Eating/drinking cues, however, may have a greater variety and complexity than physical activity cues. Firstly, in addition to visual environmental cues, there may be other sensory cues present, including olfactory and taste cues that are not as relevant in physical activity cues. Secondly, inviduals may be buying and consuming different food items from day to day, which also increases the variety of eating/drinking cues. With a greater variety of cues, individuals likely need to sharpen their cue detection and increase the specificity of these cues in their if-then plans, resulting in greater eating/drinking cue detection being associated with greater eating/drinking cue specificity at most time points. Furthermore, greater eating/drinking response specificity was associated with greater subsequent eating/drinking habit strength. This means that the eating/drinking action response needs to be more specific over time in order for the targeted eating/drinking habit to strengthen, which is logical because eating/drinking cues can be complex and thus needs to be more specific in order to be clear.

Our findings extend prior research on implementation intentions in several ways. Firstly, the present study examined the effects of the “if” and “then” components of implementation intentions separately. Other studies thus far have examined the effects of the two components together as a whole. We are also the first to examine the relationships between psychological variables (cue detection and habit strength) and the separate components of if-then plans in a longitudinal health behaviour intervention. To our knowledge, if-then plans constructed in existing health behaviour interventions were much more limited in freedom. Namely, their participants created plans using pre-determined templates and strategies for the specific behavior that they aimed to change. Some studies also limited in the quantity of plans that participants made. In the present study, participants created if-then plans that were highly individualized. Participants were guided by their lifestyle coaches to create personalized plans, choosing whichever cues that were most problematic for them. No pre-determined templates were provided. Instead, participants were guided to choose their own internal and/or cues. Therefore, plans in our intervention have more variety and flexibility than those created in existing interventions, which better reflects real life scenarios.

Limitations and Future Directions

Some limitations of the present study should be noted. Firstly, there may be a ceiling effect in the numerical codings of cue specificity, which could have influenced data analysis results of models involving cue specifity and cue detection as variables. The ceiling effect refers to the cue specificity scores to have little variance, and thus skewing the results and limiting analysis. From the data, we observed that there are many more highly specific cues than those of lower specificity. Response specificity, however, was more variable, ranging from lower to higher specificity more evenly. Among eating/drinking-related if-then plans in the carried forward database, 91.6% of cues were highly specific (coded as 2), whereas only 65.0% of responses were of low specificity (coded as 1). A similar pattern occurred in the physical activity-related if-then plans, in which 77.8% of cues were highly specific while only 64.6% were of low specificity. These findings suggest that individuals may have been skillful at identifying their problematic cues and transferring them into the if-component of their if-then plans, but they may have been less capable of finding an action response to implement in the then-component. While it may be beneficial for people to be efficient at noticing their cues in daily life and putting this skill to use, the lack of variability limits the ability to statistically analyze the data.

Secondly, the cue detection questionnaire administered in the present study had low internal consistency, particularly in its physical activity subscale, most likely due to having only two items in the subscale. To our knowledge, there was no questionnaire available in existing studies that measured cue detection that fit our purposes during the intervention period. We designed this questionnaire adapted to the needs of the present study. The small number of items and the resulting low internal consistency in the physical activity subscale of the questionnaire may be a limitation in data analysis. Future research is needed in creating and validating a questionnaire that accurately measures cue detection in health behaviour interventions.

Other possible reasons could also explain the results that did not support our hypotheses. In the present study, we treated all cues as the same in the intervention and analyses rather than teaching participants to differentiate between the varying types of cues. Ample research has shown that various types of cues could elicit eating/drinking behaviours, including external sensory and cognitive cues (Coelho, Idler, Werle, & Jansen, 2011; Elliston, Ferguson, Schüz, & Schüz, 2017; Fedoroff, Polivy, & Herman, 1997; Gaillet, Sulmont-Rossé, Issanchou, Chabanet, & Chambaron, 2013; LeGoff & Spigelman, 1987; Piqueras-Fiszman, Alcaide, Roura, & Spence, 2012; Spence, 2018; Wadhera & Capaldi-Phillips, 2014; Zellner, Lankford, Ambrose, & Locher, 2010). Environmental cues such as other people in one's environment, location, and time could elicit physical activity behaviours (Pimm et al., 2016). Furthermore, there is a lack of research in health behaviour interventions that differentiate between the above cue types, as well as between internal (e.g., emotions, physiological cues such as hunger or thirst) versus external cues. Teaching people how to respond to certain types of cues and pairing these cues with certain types of action responses could be highly beneficial in reinforcing healthy responses. As an example, imagine a participant who experiences negative thoughts after returning home from work (cognitive cue) and their impulse is to seek comfort in junk food, but they recognize that they are neither hungry nor thirsty (internal cue). Nevertheless, the cookies on their kitchen counter still look appetizing enough (visual cue) and the smell of chips that their spouse is snacking on beside them is extremely tempting (olfactory cue). If they are taught to recognize and become highly aware of these different cues, then they may have better chances of pairing the cues with a healthy action response, such as talking a walk outside or eating a fruit instead of indulging on the cookies/chips. Therefore, future interventions should tailor to this difference in cues, such as designing interventions that target visual eating/drinking and physical activity cues or interventions that focus on training participants to detect internal cues. It would be important to examine whether certain types of cues are easier to detect than others, and thus whether specifying certain types of cues may be more pertinent than other types, which could also influence the results of the analyses involving cue specificity as a variable.

Although we regard the freedom that participants were given for creating their if-then plans and individualized coaching as strengths, it is possible that these factors may also have drawbacks. Firstly, participants varied on their learning ability and pace when creating their own if-then plans. Some participants learned and understood the concept quickly and were able to apply it right away, whereas others took much longer to learn, create, and apply the plans correctly and effectively. The coaches leading the groups also improved in their coaching ability over time, which could have accelerated the participants' learning by the end of the core teaching sessions and throughout the trial.

Secondly, by giving participants freedom on creating their if-then plans, they were encouraged to select whichever problematic cue they would like. These selections were highly personalized, and it was left to the participants' own judgement what to regard as a problematic cue. Although we encouraged participants to check their calorie intake records and physical activity records (to see if there were any problematic food cues they may have missed and assumed that they did not consume as many calories, such as alcohol and nuts), we did not have methods to confirm whether these were truly the most problematic cues to target in daily life. Despite these drawbacks, training participants individually to create if-then plans as a long-term skill is still highly beneficial. However, in the short term, especially pertaining to the data we have collected, the quality of if-then plans created at the beginning sessions may not have been as high as those created later on in the intervention, which could have affected our findings.

Furthermore, future research should assess and monitor to what extent participants enacted their if-then plans in daily life throughout the study and whether those who did experienced greater changes in cue activation or habit strength than those who did not. A step further would be to ensure that they used the plans regularly by using methods such as monitoring sheets or a digital monitoring device that they wear to remind them. This could in turn further strengthen the connection between the cue and response components of the if-then plan through more frequent and repeated associations between them. Future studies should assess if-then plan use throughout the intervention and control for these discrepancies in the analyses.

To conclude, although cue specificity was expected to predict cue detection, and reciprocally, cue detection was expected to predict cue specificity in both physical activity and eating/drinking ALT models, this hypothesis was partially supported in only the eating/drinking model. Results showed that greater eating/drinking cue detection was associated with greater subsequent cue specificity at several time points. Response specificity was expected to predict habit strength, and reciprocally, habit strength was expected to predict response specificity in both physical activity and eating/drinking ALT models. This hypothesis was partially supported in both models, namely, greater physical activity habit strength was associated with subsequent lower response specificity at several time points and greater eating/drinking response specificity was associated with subsequent greater habit strength at several time points. More research is needed to examine the effects of the psychological variables of cue detection and habit strength and individual components of implementation intentions.

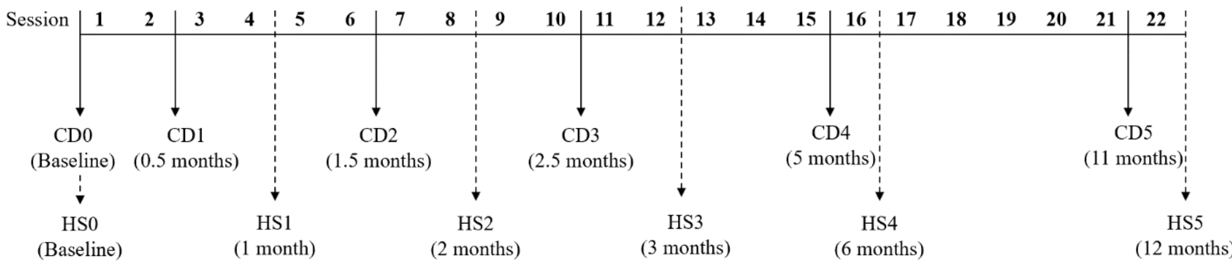

Figure 1. Measurement timeline of cue detection and habit strength. Time points of measurement are indicated below session numbers located at the top. “CD” = Cue detection. “HS”= Habit strength.

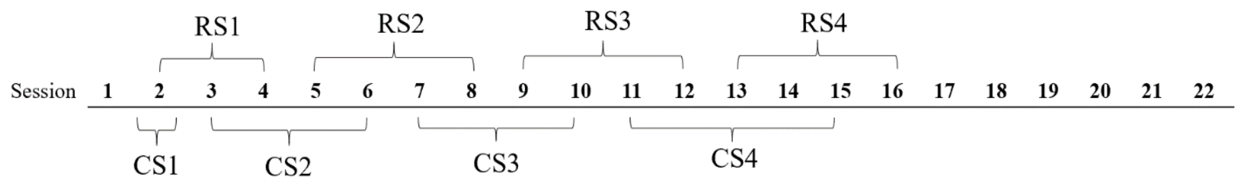

Figure 2. Timeline of aggregated scores calculations and the specific sessions from which the aggregated scores were calculated. “CS” = Cue Specificity. “RS” = Response Specificity.

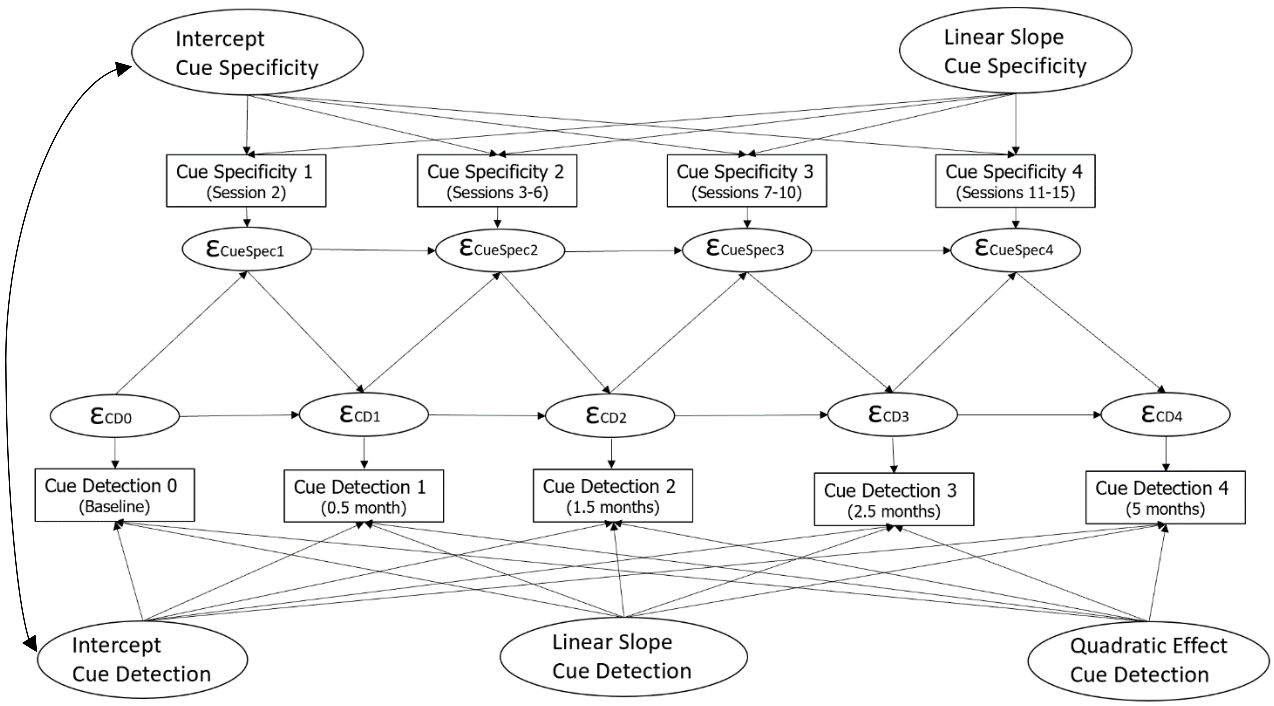

Figure 3. Autoregressive latent trajectory model with structured residuals containing relationships between cue specificity and cue detection at various time points. Figure 3 represents both Model 1 physical activity cue specificity predicting cue detection and Model 2 eating/drinking cue specificity predicting cue detection. “Cue Specificity 1” to “Cue Specificity 4” are observed cue specificity average scores. $\varepsilon_{CueSpec1}$ to $\varepsilon_{CueSpec4}$ are residuals of cue specificity average scores. “Cue detection 0” to “Cue detection 4” are observed cue detection average scores. ε_{CD0} to ε_{CD4} are residuals of cue detection. Specific time points for cue detection are indicated in brackets in each observed score. Average scores of cue specificity according to session numbers are also indicated in brackets in the observed scores. The intercepts, linear slopes, and quadratic slopes were estimated using observed repeated measures of the cue specificity and cue detection. The residuals represent the deviations of the observed repeated measures from the expected score given the underlying growth curve trajectory.

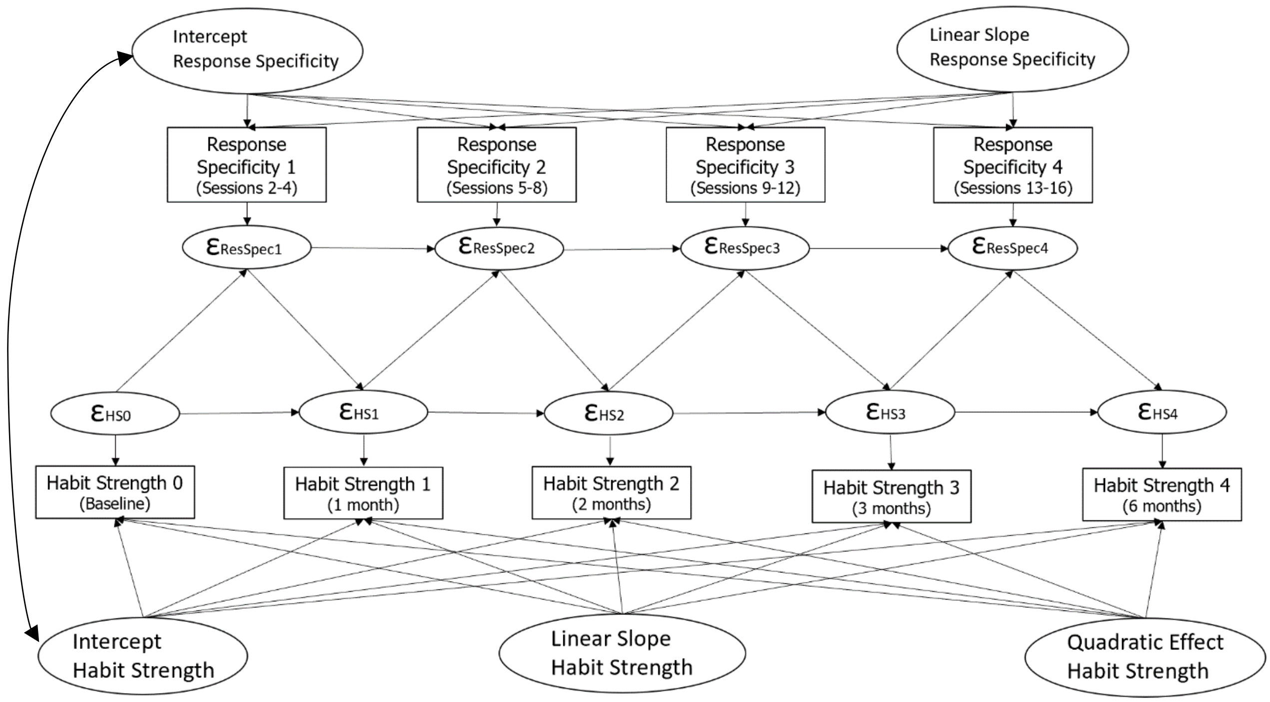

Figure 4. Autoregressive latent trajectory model with structured residuals showing relationships between response specificity and habit strength at various time points. Figure 4 represents both Model 2 physical activity response specificity predicting habit strength and Model 4 eating/drinking response specificity predicting habit strength. “Response Specificity 1” to “Response Specificity 4” are observed response specificity average scores. $\varepsilon_{ResSpec1}$ to $\varepsilon_{ResSpec4}$ are standard residuals of response specificity average scores. “Habit Strength 0” to “Habit Strength 4” are observed habit strength average scores. ε_{HS0} to ε_{HS4} indicate standard residuals of habit strength. Specific time points for habit strength are indicated in brackets in each observed score. Average scores of response specificity according to session numbers are also indicated in brackets in the observed scores. The intercepts, linear slopes, and quadratic slopes were estimated using observed repeated measures of the cue specificity and cue detection. The

residuals represent the deviations of the observed repeated measures from the expected score given the underlying growth curve trajectory.

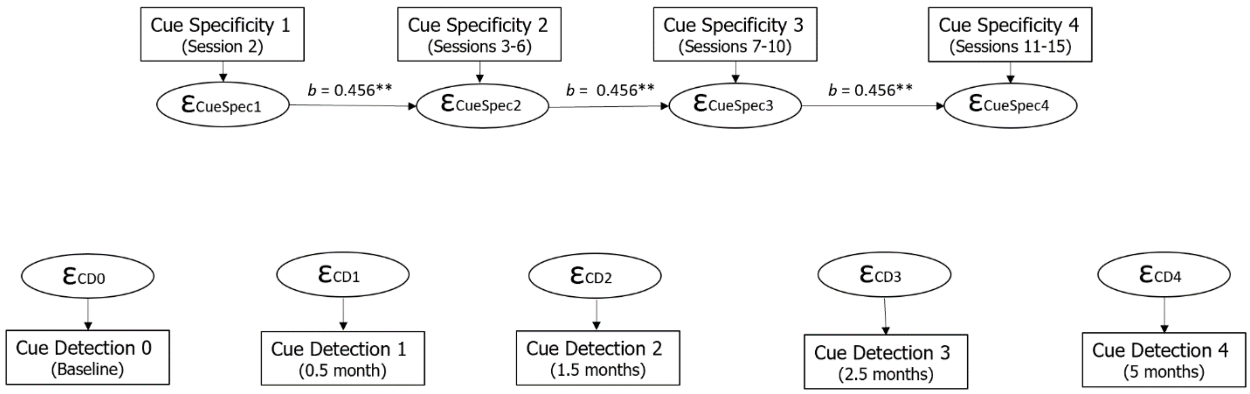

Figure 5. Significant results of the autoregressive latent trajectory model with residuals of physical activity cue specificity average scores related to physical activity cue detection at various time points. β estimates are unstandardized. *p < .01, **p < .05.

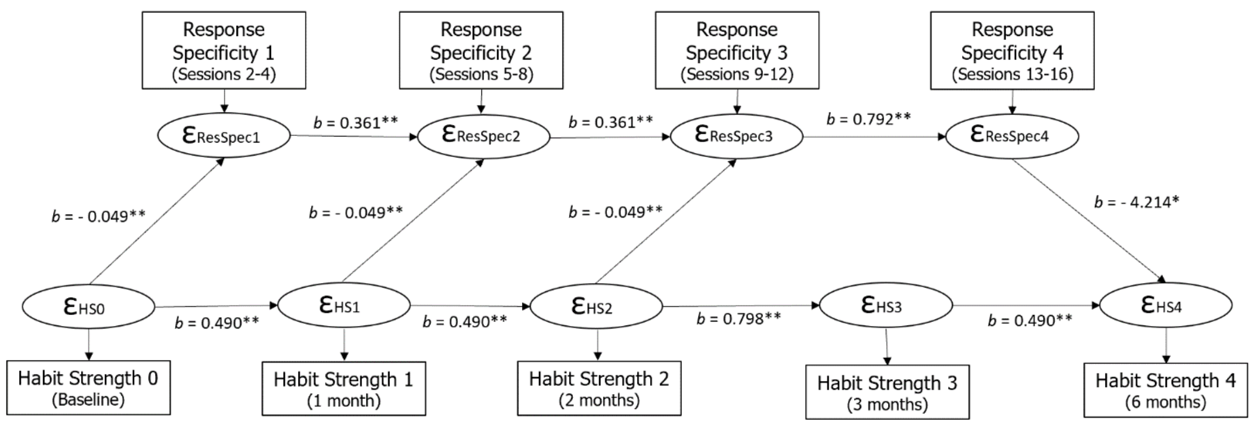

Figure 6. Significant results of the autoregressive latent trajectory model with residuals of physical activity response specificity average scores related to physical activity habit strength at various time points. β estimates are unstandardized. *p < .01, **p < .05.

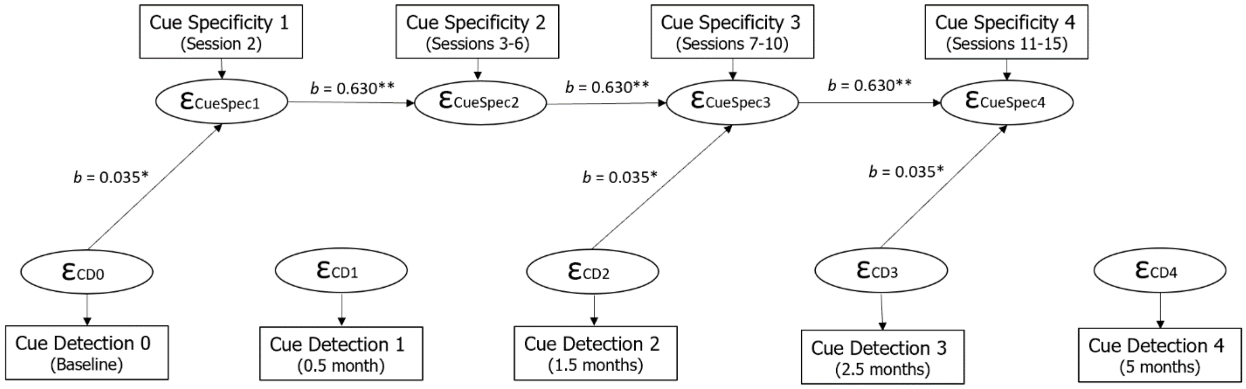

Figure 7. Significant results of the autoregressive latent trajectory model with residuals of eating/drinking cue specificity average scores related to eating/drinking cue detection. β estimates are unstandardized. *$p < .01$, **$p < .05$.

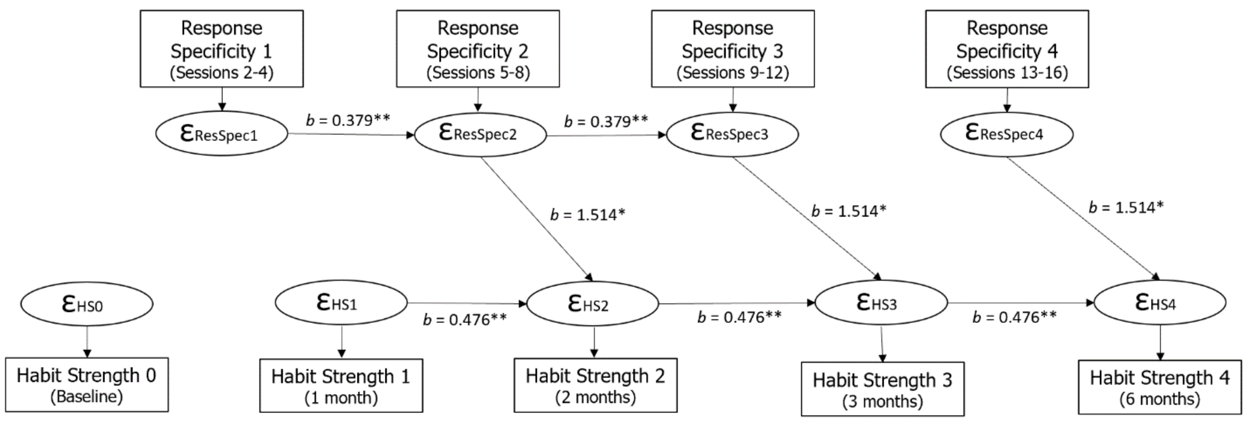

Figure 8. Significant results of the autoregressive latent trajectory model with residuals of eating/drinking response specificity average scores related to eating/drinking habit strength. β estimates are unstandardized. *$p < .01$, **$p < .05$.

Table 1. Demographics

	N = 83
Age, mean (*SD*)	49.18 (11.65)
Gender, female, *N* (%) female	71 (85.5%)
Caucasian, *N* (%)	64 (77.1%)
Married, *N* (%)	48 (57.8%)
Education, bachelor's degree *N* (%)	41 (49.4%)
Employed, *N* (%)	60 (72.3%)
Household income > $120,000, *N* (%)	17 (20.5%)
Smoker, *N* (%)	2 (2.4%)

Demographics of 83 participants who created eating/drinking behaviour-related if-then plans.

Table 2. Model 1: Physical Activity Model Results of Cue Specificity and Cue Detection

Parameter	Unstandardized Estimate (*SE*)	Standardized Estimate	*p*
Autoregressive Effects			
$CS_1 \rightarrow CS_2$	0.456** (.082)	.74	.000
$CS_2 \rightarrow CS_3$	0.456** (.082)	.76	.000
$CS_3 \rightarrow CS_4$	0.456** (.082)	.59	.000
$CD_0 \rightarrow CD_1$	0.198 (.109)	.23	.069
$CD_1 \rightarrow CD_2$	0.198 (.109)	.20	.069
$CD_2 \rightarrow CD_3$	-0.024 (.131)	-.04	.857
$CD_3 \rightarrow CD_4$	-0.024 (.131)	-.02	.857
Cross-lagged Effects			
$CD_0 \rightarrow CS_1$	0.022 (.014)	.07	.130
$CD_1 \rightarrow CS_2$	- 0.036 (.027)	-.16	.178
$CD_2 \rightarrow CS_3$	0.022 (.014)	.16	.130
$CD_3 \rightarrow CS_4$	0.022 (.014)	.13	.130
$CS_1 \rightarrow CD_1$	- 0.065 (.592)	-.02	.913
$CS_2 \rightarrow CD_2$	0.566 (.681)	.13	.406
$CS_3 \rightarrow CD_3$	- 0.065 (.592)	-.01	.913
$CS_4 \rightarrow CD_4$	- 0.065 (.592)	-.01	.913
M			
CS_{int}	1.797** (.032)	-	.000
CD_{int}	5.528** (.109)	-	.000
$CS_{linear\ slope}$	-0.008 (.005)	-	.110
$CD_{linear\ slope}$	0.096** (.023)	-	.000
Fit statistics			
χ^2	34.288		.502
df	35		
RMSEA	0.00		
CFI	1.00		

CS = cue specificity; CD = cue detection; CS_{int} = cue specificity intercept; CD_{int} = cue detection intercept; $CS_{linear\ slope}$ = cue specificity linear slope; $CD_{linear\ slope}$ = cue detection linear slope; int = latent intercept; linear slope = latent linear growth rate; RMSEA = = root mean square error of approximation; CFI = comparative fit index.

*p < .05. **p < .01.

Table 3. Model 2: Physical Activity Model Results of Response Specificity and Habit Strength

Parameter	Unstandardized Coefficient (*SE*)	Standardized Coefficient	*p*
Autoregressive Effects			
$RS_1 \rightarrow RS_2$	0.361** (.13)	.57	.005
$RS_2 \rightarrow RS_3$	0.361** (.13)	.41	.005
$RS_3 \rightarrow RS_4$	0.792** (.12)	.73	.000
$HS_0 \rightarrow HS_1$	0.490** (.18)	-.21	.006
$HS_1 \rightarrow HS_2$	0.490** (.18)	.49	.006
$HS_2 \rightarrow HS_3$	0.798** (.12)	.69	.000
$HS_3 \rightarrow HS_4$	0.490** (.18)	.46	.006
Cross-lagged Effects			
$HS_0 \rightarrow RS_1$	- 0.049** (.02)	-.21	.004
$HS_1 \rightarrow RS_2$	- 0.049** (.02)	-.33	.004
$HS_2 \rightarrow RS_3$	- 0.049** (.02)	-.37	.004
$HS_3 \rightarrow RS_4$	0.003 (.01)	.02	.836
$RS_1 \rightarrow HS_1$	- 0.971 (.54)	-.23	.069
$RS_2 \rightarrow HS_2$	- 0.971 (.54)	-.14	.069
$RS_3 \rightarrow HS_3$	- 0.381 (1.03)	-.04	.712
$RS_4 \rightarrow HS_4$	- 4.214* (1.74)	-.48	.015
M			
RS_{int}	1.683** (.032)	-	.000
HS_{int}	2.874** (.155)	-	.000
$RS_{linear\ slope}$	- 0.012** (.004)	-	.009
$HS_{linear\ slope}$	0.728** (.097)	-	.000
$HS_{quadratic\ slope}$	- 0.085** (.015)	-	.000
Fit statistics			
χ^2	51.633		.027
df	34		
RMSEA	0.080		
CFI	0.958		

RS = response specificity; HS = habit strength; RS_{int} = response specificity intercept; HS_{int} = habit strength intercept; $RS_{linear\ slope}$ = response specificity linear slope; $HS_{linear\ slope}$ = habit strength linear slope; $HS_{quadratic\ slope}$ = habit strength quadratic slope; int = latent intercept; linear slope = latent linear growth rate; RMSEA = = root mean square error of approximation; CFI = comparative fit index.

*$p < .05$. **$p < .01$.

Table 4. Model 3: Eating/Drinking Behaviours Model Results of Cue Specificity and Cue Detection

Parameter	Unstandardized Coefficient (*SE*)	Standardized Coefficient	*p*
Autoregressive Effects			
$CS_1 \rightarrow CS_2$	0.630** (.102)	.89	.000
$CS_2 \rightarrow CS_3$	0.630** (.102)	.86	.000
$CS_3 \rightarrow CS_4$	0.630** (.102)	.79	.000
$CD_0 \rightarrow CD_1$	0.099 (.075)	.17	.190
$CD_1 \rightarrow CD_2$	0.012 (.113)	.01	.916
$CD_2 \rightarrow CD_3$	0.099 (.075)	.10	.190
$CD_3 \rightarrow CD_4$	- 0.099 (.194)	-.10	.608
Cross-lagged Effects			
$CD_0 \rightarrow CS_1$	0.035* (.016)	.11	.027
$CD_1 \rightarrow CS_2$	- 0.001 (.018)	.00	.938
$CD_2 \rightarrow CS_3$	0.035* (.016)	.13	.027
$CD_3 \rightarrow CS_4$	0.035* (.016)	.16	.027
$CS_1 \rightarrow CD_1$	0.030 (.274)	.02	.911
$CS_2 \rightarrow CD_2$	0.871 (.744)	.31	.242
$CS_3 \rightarrow CD_3$	0.871 (.744)	.23	.242
$CS_4 \rightarrow CD_4$	0.871 (.744)	.19	.242
M			
CS_{int}	1.910** (.020)	-	.000
CD_{int}	5.574** (.087)	-	.000
$CS_{linear\ slope}$	0.002 (.003)	-	.544
$CD_{linear\ slope}$	0.293** (.068)	-	.000
$CD_{quadratic\ slope}$	- 0.034** (.012)	-	.005
Fit statistics			
χ^2	33.784		.429
df	33		
RMSEA	0.017		
CFI	0.997		

CS = cue specificity; CA = cue detection; CS_{int} = cue specificity intercept; CA_{int} = cue detection intercept; CS_{slope} = cue specificity slope; CA_{slope} = cue detection slope; int = latent intercept; linear slope = latent linear growth rate; RMSEA = = root mean square error of approximation; CFI = comparative fit index.

*p < .05. **p < .01.

Table 5. Model 4: Eating/Drinking Behaviours Model Results of Response Specificity and Habit Strength

Parameter	Unstandardized Estimate (*SE*)	Standardized Estimate	*p*
Autoregressive Effects			
$RS_1 \rightarrow RS_2$	0.379** (.111)	.65	.001
$RS_2 \rightarrow RS_3$	0.379** (.111)	.67	.001
$RS_3 \rightarrow RS_4$	- 0.391 (.791)	-.46	.622
$HS_0 \rightarrow HS_1$	- 0.658 (.456)	-.99	.148
$HS_1 \rightarrow HS_2$	0.476** (.129)	.26	.000
$HS_2 \rightarrow HS_3$	0.476** (.129)	.52	.000
$HS_3 \rightarrow HS_4$	0.476** (.129)	.41	.000
Cross-lagged Effects			
$HS_0 \rightarrow RS_1$	- 0.094	.07	.165
$HS_1 \rightarrow RS_2$	0.027	.02	.096
$HS_2 \rightarrow RS_3$	0.027	.02	.096
$HS_3 \rightarrow RS_4$	0.059	.03	.068
$RS_1 \rightarrow HS_1$	- 0.882	.69	.200
$RS_2 \rightarrow HS_2$	1.514*	.65	.019
$RS_3 \rightarrow HS_3$	1.514*	.65	.019
$RS_4 \rightarrow HS_4$	1.514*	.65	.019
M			
RS_{int}	1.672** (.030)	-	.000
HS_{int}	3.203** (.110)	-	.000
$RS_{linear\ slope}$	- 0.011** (.005)	-	.031
$HS_{linear\ slope}$	0.772** (.085)	-	.000
$HS_{quadratic\ slope}$	- 0.090** (.013)	-	.000
Fit statistics			
χ^2	57.076		.002
df	30		
RMSEA	0.104		
CFI	0.911		

RS = response specificity; HS = habit strength; RS_{int} = response specificity intercept; HS_{int} = habit strength intercept; $RS_{linear\ slope}$ = response specificity linear slope; $HS_{linear\ slope}$ = habit strength linear slope; $HS_{quadratic\ slope}$ = habit strength quadratic slope; int = latent intercept; linear slope = latent linear growth rate; RMSEA = = root mean square error of approximation; CFI = comparative fit index.

*p < .05. **p < .01.

Table 6. Descriptive statistics for cue specificity and cue detection observed average scores in the physical activity model.

Variable	1	2	3	4	5	6	7	8	9
1. Cue Specificity 1	-								
2. Cue Specificity 2	.89**	-							
3. Cue Specificity 3	.82**	.91*	-						
4. Cue Specificity 4	.73	.77**	.91**	-					
5. Cue Detection 0	-.01	-.10	-.09	-.09*	-				
6. Cue Detection 1	-.04	-.09	-.04	.03	.52**	-			
7. Cue Detection 2	.06	.09	.12*	.07	.41**	.53**	-		
8. Cue Detection 3	.01	.07	.07	.10	.44**	.55**	.51**	-	
9. Cue Detection 4	-.07	.00	.00	.01	.45**	.43**	.53**	.61**	-
M	1.74	1.80	1.79	1.77	5.50	5.47	5.76	5.79	5.99
SD	.38	.28	.26	.25	1.16	1.17	2.41	.90	.81

Note: $N = 81$.
*$p < .05$. **$p < .01$.

Table 7. Descriptive statistics for response specificity and habit strength observed average scores in the physical activity model.

Variable	1	2	3	4	5	6	7	8	9
1. Response Specificity 1	-								
2. Response Specificity 2	.83	-							
3. Response Specificity 3	.75**	.86*	-						
4. Response Specificity 4	.65	.74**	.90	-					
5. Habit Strength 0	-.19	-.19	-.19	-.17	-				
6. Habit Strength 1	-.16	-.22	-.18	-.10*	.70**	-			
7. Habit Strength 2	-.33	-.31	-.32	-.26*	.44**	.75**	-		
8. Habit Strength 3	-.25	-.29	-.30	-.25	.51**	.67**	.82**	-	
9. Habit Strength 4	-.11	-.18	-.21	-.27	.40**	.62**	.61**	.65**	-
M	1.65	1.70	1.64	1.61	2.86	3.43	4.07	4.32	4.25
SD	.36	.27	.26	.25	1.34	1.45	1.39	1.46	1.70

Note: $N = 81$.
*$p < .05$. **$p < .01$.

Table 8. Descriptive statistics for cue specificity and cue detection observed average scores in the eating/drinking behaviours model.

Variable	1	2	3	4	5	6	7	8	9
1. Cue Specificity 1	-								
2. Cue Specificity 2	.88**	-							
3. Cue Specificity 3	.79	.90	-						
4. Cue Specificity 4	.74*	.83	.87	-					
5. Cue Detection 0	.08	.08	-.04	-.01	-				
6. Cue Detection 1	-.04	-.08	-.10	-.10	.38**	-			
7. Cue Detection 2	.22	.16	.19	.12	.24	.42**	-		
8. Cue Detection 3	.03	.01	.02	.04	.23	.53**	.57**	-	
9. Cue Detection 4	-.02	.04	.02	-.06	.35*	.26	.58**	.41**	-
M	1.88	1.90	1.91	1.91	5.56	5.71	5.97	6.07	6.17
SD	.28	.19	.14	.12	.93	.74	.69	.66	0.62

Note: $N = 83$.
*$p < .05$. **$p < .01$.

Table 9. Descriptive statistics for response specificity and habit strength observed average scores in the eating/drinking behaviours model.

Variable	1	2	3	4	5	6	7	8	9
1. Response Specificity 1	-								
2. Response Specificity 2	.73	-							
3. Response Specificity 3	.54	.91	-						
4. Response Specificity 4	.52	.73	.86	-					
5. Habit strength 0	-.08	-.11	-.04	.09	-				
6. Habit strength 1	.01	.02	.10	.09	.34**	-			
7. Habit strength 2	.20	.14	.20	.23	.32**	.51	-		
8. Habit strength 3	.24	.09	.11	.18*	37**	.61**	.77**	-	
9. Habit strength 4	.03	-.12	-.03	.07	.39**	.62**	.63**	.67**	-
M	1.70	1.67	1.65	1.62	3.19	3.87	4.36	4.73	4.65
SD	.31	.25	.24	.23	1.14	1.02	1.02	1.23	1.34

Note: $N = 83$.
*$p < .05$. **$p < .01$.

Appendix B

McGill CHIP Healthy Weight Program
If-Then Plans Specificity Dichotomous Coding Instructions

Low Specificity
If the cue/response **can** be more specifically described and questions are left to be answered **code 1**.

Ex RESPONSE: "… then I will be conscious of how much I eat." the person did not specify how much he/she will eat
Ex RESPONSE: "… then I will eat something else." the person did not specify what else he/she will eat
Ex RESPONSE: "… then I will try new types of exercise to stimulate me more." the person did not specify what types of exercise he/she will try
Ex RESPONSE: "… then I will go to the gym on Saturday OR Sunday." the person did not specify on which day he/she will go to the gym
Ex RESPONSE: "…then I will eat smaller portions." the person did not specify how much smaller the portions will be
Ex RESPONSE: "…then I will focus on the good things about my meal." the person did not specify the type of good things he/she was referring to.
Ex RESPONSE: "…then I will stop eating when I'm full." the person did not specify when he/she will be full.
Ex RESPONSE: "…then I will try not to…", "…then I should…", "…then I would…", "…then I need to have…" → the words TRY TO, SHOULD, WOULD, NEED TO HAVE, WANT TO, I CAN (not referring to cravings), I WILL REMEMBER TO, I AM ABLE TO leave uncertainty for whether the action will be enacted or not

Note: Responses with "THEN I will PLAN…" must specify <u>when</u> and <u>how</u> they planned.

Ex RESPONSE: "… I will plan my meals and snack time ahead of time" – did not clarify when exactly the planning will happen, **code 1**

Ex RESPONSE: "… I will plan a 15 min. break to snack so that I don't get overly hungry" – 15 minute break is specific enough, **code 2**

Note: Responses such as "then I will choose something <u>appropriate</u>", "then I will eat <u>less</u>", "then I will exercise <u>more</u>", "I will weigh and measure (my food) <u>to be conscious</u>", "if I'm eating <u>too much</u>" are not sufficiently specific **code 1**.

Note: Cues that are vaguely worded, such as "If I want to…" could be **coded either 1 or 2**.

The following cues are very abstract things that people want to do, **code 1**

Ex CUE: "If I want to be active as a way to be social…"

Ex CUE: “If I want to increase my exercise…”
Ex CUE: “If I want to be healthy…”
Ex CUE: “If I want to live a good life…”
Ex CUE: “If I want to stay in control and not feel deprived…”
Ex CUE: “If I want to lose weight during holidays…”

The following cues are similar to hunger cues, specific so **code 2**

Ex CUE: “If I want to have a snack….”
Ex CUE: “If I want to eat something….”

Note: If the word "healthier" or "healthy" is used in the response, then the response must contain other highly specific actions, such as "stopped eating" or "get up to go to the kitchen" or give an example of the healthier alternative to be coded as 2 for high specificity.

Ex RESPONSE: “…THEN I will look for a healthier alternative (ex. Rice crackers)” → provides rice crackers as an example, **code 2**

Ex RESPONSE: “IF I find myself eating in the evening watching TV, THEN I will stop, + if I really need to eat I will go to kitchen + find a healthier alternative” →provides additional details to finding healthier alternative – “I will stop” and “I will go to kitchen”, **code 2**

Ex RESPONSE: "…THEN I will choose a healthier option than dumplings" → **code 1**

Note: In the above example, when response is a comparison between two food options, must indicate <u>what</u> the "healthier" foods they will choose. In this case, dumplings.

Ex RESPONSE: If the response is only "I will choose something <u>healthier</u>" or "I'll look for <u>healthy alternatives</u>", or “I will eat light the rest of the day”. → too vague, **code 1**

Note:
Need to specify *quantity* of healthier alternative for foods that are high in calorie/fat: e.g., herbal tea is not fattening, so it does not matter how much they drink, no need to specify quantity, **code 2**.

However, if the plan says "I will eat more fruits"; "I will eat more nuts"- some fruits have high sugar content, not as healthy and will contribute to weight gain, **code 1** if they does not specify how much more fruits (e.g., 2 pieces vs the whole watermelon" or "a handful of nuts vs unlimited nuts").

Note:

Cues or responses involving "overeat" could mean subjectively feeling that they over ate, OR it could also mean that they went exceeded their daily calorie/fat budget – **code 1**

> Ex RESPONSE: "… I will have some but will be choosey about what I eat and will be careful not to overeat"

However, if "overeat" is a hunger cue instead of referring to the subjective feeling of overeating, **code 2**

> Ex CUE: "WHEN I am really hungry and feel like I will overeat…."

High Specificity
If the cue/response **cannot** be more specifically described and all questions are answered **code 2**

> Ex CUE: "If I am eating Doritos …" What is the person eating? Doritos.
> Ex CUE: "If I am craving chocolate …" What is the person craving? Chocolate.
> Ex CUE: "If my kids are ordering pizza …" What is the person's kids doing? Ordering Pizza.
>
> Ex RESPONSE: "… then I will have an apple instead" What will the person have instead? An apple.
> Ex RESPONSE: "… then I will go to the gym on Saturday morning for an hour." What will the person do? Go to the gym on Saturday morning for an hour.
> Ex RESPONSE: "…then I will buy a low-calorie brand" What will the person buy? A low-calorie brand. → This is referring to a choice between "low fat/calorie" vs "regular" brands, in which the comparison is made for the participant already, so it is highly specific

Note: "**Gym**" is considered to be sufficiently specific as a CUE, **code 2**.
Ex CUE: "If I go to the gym…"

"Gym" is NOT considered to be sufficiently specific as a RESPONSE, **code 1**.
Ex RESPONSE: "…then I will go to the gym." the person did not specify the **duration** of his/her attendance at the gym, nor was the **time/day** specified.

Note: For if-then plans about **any** type of physical activity, the **duration** of the exercise or movement <u>must be indicated</u> to be given a code of 2. This includes activities such as walking the dog, taking the stairs, etc.
Exception: When the participant is going somewhere specific with a <u>limited</u> duration, **code 2**
Ex RESPONSE: "… then I will walk from McIntyre building to Peel metro."

Note: "**Weekend**" is sufficiently specific if the behavior is likely to occur on both days of the weekend:
Ex CUE: "If I drink my coffee on the weekend…" there is no need to specify a particular day, **code 2**

Ex RESPONSE: "…then I will go to the gym on the weekend." **code 1**

Note: Ex CUE: "If I crave a high calorie snack, …", **code 2**.
Note: Ex RESPONSE: "… then I will eat a low-calorie snack.", **code 1** → in this example, we trust that participants are capable of making the decision of whether a snack is low calorie or not due to the psychoeducation they received in the program.

Note: If the <u>cue</u> can be more specific, but that specification is indicated in the THEN portion of the plan **code 2**
Ex: If I eat nuts, then I will only take a handful.

Note: It is NOT necessary to further specify the name/type of restaurant, the name/type of dessert, the name/type of meal, the name/type of sweet food, etc. for a coding of "2".

Note: "… then I will measure the amount of food."
→ need to specify the *quantity* they will measure exactly e.g., 1 or 2 tablespoons of sugar to **code 2**
→ if only said "…then I will measure the amount of food" without quantity specified, **code 1**

Note: "…then I will eat slowly and consciously." It is NOT necessary to specify how slowly he/she will eat. **code 2**

Note: The person <u>must</u> specify when he/she will track their food to receive a code of "2"

Note: Plans involving "reminders":
These plans remind participants e.g., to eat mindfully or to set an alarm. It can be assumed that they already know that they will likely forget to perform the associated response/action without a reminder, so a reminder plan is a conscious cognitive strategy/action, **code 2**.

> Ex RESPONSE: "… THEN I will remind myself of goal & risk 1 drink can have on inhibitions (& stay on track)", **code 2**.
>
> Ex RESPONSE: "… THEN I will choose portion size from fridge list and remind self that portion is enough for real hunger", **code 2**.

Note: "… as soon as I finish the meal" specifies when they will track their food intake, **code 2**.

Note: If a plan component is unclear and coders must interpret/guess what the plan means, **code 1**,

Note: Regarding weighing plans, do NOT penalize plan if they do not specify in response when they will weigh themselves. **Code 2** for response as long as they say some variation of "I will weigh myself". However, they must have a highly specific cue to obtain a coding of 2 highly specific for the response of "I will weigh myself".

Chapter 4: General Discussion

As more behaviour change interventions are designed and implemented in various populations around the world, and more empirical evidence is reported that demonstrates the higher efficacy of theory-based interventions, there is still a need to understand the underlying processes and mechanisms that lead to behaviour change. Existing studies to date mostly examine behaviour change outcomes directly. However, less is known about the role of psychological factors, namely cue detection and habit strength, in the process leading to behaviour change. Furthermore, closer investigation is required to examine how cue detection and habit strength make an impact in the change process, namely through implementation intentions. In this dissertation, I investigated the underlying mechanisms of the process of change that address this gap in the literature. More specifically, the purpose of this research project was to examine the role of cue detection and habit strength in the process leading to behaviour change, as well as to examine how the specificity of implementation intentions influence their role. I integrated my two studies into a randomized controlled trial, a year-long lifestyle habit and weight loss intervention to address the role of cue detection and habit strength in a longitudinal intervention. All participants completed questionnaires that measure cue detection and habit strength throughout the intervention, as well as tracked and self-reported their food/drink consumption and physical activity steps using a pedometer provided for them. The results of this longitudinal study were reported in two studies, both addressing the two purposes mentioned above to address the gap in the literature on this process of change.

Study 1 Findings and Significance

In the first study, we tested whether changes in cue detection and habit strength predicted behaviour change and eventual weight loss. We formed hypotheses at both the between- and within-person level. At the between-person level, we hypothesized that both cue detection and habit strength will increase, whereas average calorie intake will decrease (in the eating/drinking behaviours model) and physical activity steps will increase (in the physical activity behaviours model), leading to eventual weight loss. At the within-person level, we hypothesized that all cross-lagged relationships between cue detection, habit strength and eating/drinking behaviours, and weight will be significant and mutually influence one another.

Our findings showed that some paths between repeated measures of the four variables at both the within- and between-person level to be significant. At the between-person level, all hypothesized patterns of growth in each variable were confirmed. Specifically, cue detection, habit strength, and average steps increased over time, while average calorie consumption and weight decreased over the treatment period. At the within-person level, greater habit strength led to subsequent greater cue detection at later time points in the intervention in both the physical activity and eating/drinking models. In the eating/drinking behaviours model, higher levels of habit strength were also associated with weight loss at later time points, indicating that habit strength is also a driving force toward the final outcome of weight loss.

To date, most behaviour change interventions have focused on obtaining behavioural outcomes. They are usually shorter in duration and target one or a few specific behaviours in controlled settings. More research is needed to further explore the mechanisms of change that lead to behaviour change in real-life contexts, specifically how psychological factors like cue detection and habit strength influence behaviour change. To understand the underlying processes that drive this change, the current study is the first to specifically examine the role of cue detection and habit strength in behaviour change in a longitudinal lifestyle behaviour intervention. The findings from our studies show that habit strength plays a pertinent role in this process, as reflected by the significant relationship between greater habit strength leading to subsequently greater cue detection at later time points in both the physical activity and eating/drinking behaviours models. However, the results did not show the anticipated effect between greater habit strength and higher quantity of average steps, neither did any effect show between average steps and weight loss. Nevertheless, our findings establish habit strength as a driving force in the process of change toward the eventual outcome of weight loss, emphasizing the importance of habit formation and behaviour regulation.

Study 1 Limitations and Future Directions

In the first study, we developed a questionnaire to measure cue detection because no other study existed in the literature that could be implemented in our intervention. However, the challenging with creating a new measure is choosing appropriate questionnaire items based on the health behaviours that were targeted in the intervention. Before selecting the five eating/drinking and physical activity behaviours, we thoroughly reviewed existing research for empirical evidence that would demonstrate which target eating behaviours are most relevant to successful weight loss, but we found that no such evidence yet existed (Carter & Jansen, 2012). Therefore, we selected five eating/drinking behaviours and two physical activity behaviours based on the most targeted and emphasized health behaviours in the intervention manual. We limited the number of items to reduce participant load when completing the measures. The physical activity subscale contains only two items, resulting in low internal consistency for this subscale, which could skew the analyses results. Another potential limitation could be the actual behaviours that we selected, meaning that there may be more suitable physical activity and eating/drinking behaviours that are more representative of behaviour change for losing weight.

In this study, we hypothesized that greater cue detection will lead to greater habit strength in both physical activity and eating/drinking models. However, contrary to what was expected, our findings did not show this effect. A possible reason is that there may be mediators and/or moderators that could explain the missing link between cue detection and habit strength. As an example, a possible mediator could be self-efficacy in that the participants with higher cue detection could have higher self-efficacy, and as a result form greater habit strength. Potential moderators could also be an influencing factor, such as personality traits such that those who are more conscientious could have a stronger relationship between cue detection and habit strength. Future research could explore multi-level mediation and/or moderation models that examine what connects cue detection with habit strength.

A second hypothesis that was not supported was the relationship between greater habit strength leading to behaviour change, namely physical activity average steps and average calorie consumption. There may be three potential contributors to this finding. Firstly, to better represent the tracking data, the frequency and duration of tracking behaviour change may need to be increased to more than one week of tracking and to more than three time points throughout the intervention. Secondly, tracking through self-report may not be a reliable method of measurement, possibly due to people tracking much later than the time of food/drink consumption, causing recall bias. Finally, a third potential reason could be that people may have intentionally under-reported their food/drink consumption due to feelings of guilt or embarrassment, especially if they tracked all their consumption throughout the day at the end of the day, which could exacerbate these negative feelings upon seeing the total calorie/fat gram count. Future research could take advantage of advanced tracking technology, such as ecological momentary assessment (EMA) methodologies (Shiffman, Stone, & Hufford, 2008) that involve repeated sampling of eating and drinking behaviours in real time in people's daily life environments. Suitable EMA tools could be electronic bracelets or watches that people could wear, and even better if they could send regular auditory or visual text reminders to track their food/drink intake.

Study 2 Findings and Significance

With evidence suggesting that habit strength has substantial influence on behaviour change, I then set out to examine the role of specificity of the separate components of implementation intentions, the "if" and "then" parts (which we also call cue and response parts interchangeably) on cue detection and habit strength, respectively. To our knowledge, the present study is the first to examine specificity of implementation intentions in separate components, and the first to examine relationship between implementation intention components and psychological factors. Existing studies on the effects of implementation intentions tend to be much more limited in freedom, meaning that pre-determined templates/strategies are oftentimes used. The quantity of if-then plans that participants can make and the number of behaviours that one can choose to target may also be pre-determined. In the current study, no pre-determined templates were provided. Instead, participants were guided to choose their own internal and/or cues and corresponding action responses. Taken together, the variability and flexibility provided in the present study better represents real-life contexts, which fills an important gap in the behaviour change literature.

In this study, we tested the hypothesized bidirectional relationships between cue specificity and cue detection, as well as between response specificity and habit strength. We analyzed the data in two autoregressive latent trajectory (ALT) models and found our predictions to be partially supported. In the physical activity model, greater habit strength was associated with subsequently lower levels of response specificity at most time points. In the eating/drinking model, higher response specificity led to subsequently greater habit strength at later time points in the intervention observation period, while greater cue detection led to subsequently greater cue specificity. The findings indicated that the eating/drinking model fared better than the physical activity model. In particular, none of the hypothesized bidirectional relationships were significant in the physical activity model of cue specificity and cue detection. A possible contributor to this difference between the two models could be the that physical activity and eating/drinking cues vary tremendously. Eating/drinking cues may require high acuity to be noticed due to their large variety, complexity, and unpredictability, whereas physical activity cues could be simpler, more consistent, and lower in quantity.

Study 2 Limitations and Future Directions

Although we found our hypotheses to be partially supported, it is still important to examine potential reasons for the non-supported links in the hypothesized bidirectional relationships, particularly in the models involving cue specificity and cue detection. A ceiling effect in cue specificity ratings may be a contributing factor. This effect refers to the cue specificity scores to have little variance, and thus skewing the results and limiting analysis. Descriptive statistics analyses showed that the amount of highly specific physical activity and eating/drinking cues is much higher than the amount of highly specific responses. These findings indicate that participants may have been very proficient at identifying problematic cues and then targeted these cues in their implementation intentions, but they may be less efficient at matching these cues with a healthy action response. Although it may be beneficial to for people to have higher cue acuity, the lack of variety in cues may be limiting to analyses. Participants were coached to select problematic cues, but they were not trained to differentiate varying types of cues and thus have not been able to pair corresponding action responses as skillfully. Future interventions should teach and train their participants how to differentiate between various types of cues and pair them with suitable action responses. Lastly, it would be important to measure to what extent participants enacted their plans in their daily life or whether those who did experienced greater changes in cue detection and habit strength than those who did not. Hence, future research should assess if-then plan use.

Overall Theoretical Implications

Altogether, various theoretical implications arose from this dissertation research. Firstly, habit strength emerged as an important variable in the process of habit formation in both the physical activity and eating/drinking behaviours models in both studies in this thesis. Although not all hypothesized paths in the models were supported, habit strength consistently formed significant pathways with other variables in the models.

Regarding the first study, more research is needed to examine how cue detection and habit strength are related. Potential mediators or moderators could explain the missing link between them in our results, such as self-efficacy or consciousness, to name a few. To date, there is a lack of existing studies that specifically examine mediators/moderators that affect the relationship between cue detection and habit strength in an eating/drinking and physical activity behaviours context. Furthermore, future research in which cue detection is measured could create more items that assess other aspects of mindfulness in addition to conscious awareness, including non-judgmental observations and cognitive defusion (non-avoidance of uncomfortable or negative thoughts). Finally, more research is also needed to examine how habit strength translates into change in both eating/drinking and physical activity behaviours leading to eventual weight loss. Perhaps, separate studies investigating one relationship between two variables at a time can enhance the understanding of how cue detection, habit strength, and behaviour change connect to one another.

In the second study, we further investigated the relationship between separate cue and response components of if-then plans and cue detection and habit strength, respectively. Results showed that higher eating/drinking response specificity was associated with subsequent greater habit strength in the physical activity model. This could mean that response specificity may be more important than cue specificity in the physical activity behaviour-related if-then plans, which suggests that people should create highly specific responses in their action behavioural responses to increase the likelihood of implementation of the plan and its effectiveness.

In general, there was no overall pattern shown in our results, and thus it is not feasible to make finite and specific conclusions and implications for future behavioural change interventions on weight loss. In fact, it is extremely challenging to identify which precise variables, factors, or behaviours that are most relevant to weight loss, as past research has indicated as well (Carter & Jansen, 2012). The results showed that real life is complex with multiple reasons that may contribute to behaviour change leading to weight gain or loss. Among existing studies, this type of research was usually conducted under controlled and pre-determined conditions over the short term. To our knowledge, we were the first to conduct a large-scale longitudinal behaviour lifestyle intervention that allowed high variability and flexibility in participants' choice of the types of physical activity and eating/drinking cues and if-then plans creation. Our objective was to bring the knowledge obtained from the aforementioned smaller-scale studies with controlled conditions on behaviour change and then apply it in real-life conditions. The results were highly complex, which reflected the real world. We have encountered challenges that were much more complex than studies conducted in controlled lab or field settings.

From the results of our studies, we found that eating/drinking habits were important to maintain to lose weight. We could also infer that it is important to stay vigilant to detect both physical activity and eating/drinking cues, even after new habits have already formed, which could prevent oneself from slipping back into old behaviour patterns and habits. Overall, our results provided insight on the psychological mechanisms that can lead to behaviour change and contribute to improving future behaviour change interventions, including weight loss interventions. More research is needed to determine how habit strength translates into behaviour change given that we found a direct significant relationship between habit strength and weight, but not between habit strength, behaviour change, and weight.

In summary, multiple factors could contribute to habit formation in real life settings over the long term. The role that cue detection and habit strength play in the process leading to behaviour change was highly complex and at times in directions different than what was hypothesized, which reflected the complexity of real-life conditions. Implementation intentions can be effective but not equally effective in all contexts. In the present studies, we found different results between eating/drinking and physical activity behaviours models. Although there was no definitive pattern in our results, the eating/drinking models fared slightly better than the physical activity models (more significant paths in the former than the latter, and one of the hypotheses was supported in eating/drinking response specificity and habit strength model).

Overall Limitations and Future Directions

Despite the contributions of this research to existing literature, a few noteworthy limitations should be considered. First, generalizability of our findings may be limited due to limited variability in gender, age, and ethnicity of our participants. Our participants were all recruited locally, most of whom were female, older Caucasian adults. Researchers who would like to replicate results in future lifestyle behaviour interventions should target a wider range of ethnicities and age groups, perhaps in different languages in various countries around the world during their recruitment process. More male participants are also needed, although weight loss interventions usually appeal to women more so than men because they can be seen as "female dominated services", which can make men feel deterred from continuing sessions (Elliott, Gillison, & Barnett, 2020). Future interventions should be designed interventions that are more compatible with male attitudes and thus can attract more male participants.

In addition to widening demographic characteristics, different if-then plans' specificity coding methods can also be explored. In the second study, we coded if-then plans using a dichotomous coding system that we developed for this study. However, analytic issues such as the ceiling effect in cue specificity have limited our analyses. We also coded a portion of the if-then plans following a coding system that assigns points for each specific part of the plan in order to obtain a total sum of points (e.g., one point for specifying one's location or time of meal), based on the coding system developed by Dombrowski and colleagues (Dombrowski, Endevelt, Steinberg, & Benyamini, 2016). The higher the sum of points is, the more specific we assume the plan to be. However, due to limited time and labour resources to code thousands of if-then plans and then improve inter-rater reliability, we decided to focus on analyses using only on the dichotomous specificity codings. In future research, investigators should explore alternative coding systems that could result in more variability in specificity ratings, and at the same time, have better representation of the full range of cue specificity scores as supposed to dichotomous coding.

Conclusion

The main purpose of this research was to examine the underlying process and mechanisms that lead to behaviour change, namely the role of cue detection and habit strength in this process. We found support for some cross-lagged relationships from greater habit strength to greater cue detection in both physical activity and eating/drinking behaviour models. In addition, we found that greater habit strength also led to weight loss at a few time points. Therefore, our findings highlight the important role that habit strength serves in the processing leading to behaviour change. A secondary objective of this research was to examine the impact of implementation intentions on psychological factors (i.e., cue detection and habit strength). Namely, we examined how the specificity of the “if” and “then” parts of implementation intentions mutually influence cue detection and habit strength, respectively. Our findings suggest that the bidirectional relationship between response specificity and habit strength fared better than between cue specificity and cue detection overall, which provides insight into the potential theoretical reasons for this difference in results. This research contributes to our growing knowledge about what it takes for behaviour change to occur in interventions that simulate real-life contexts, which will inform new ways to improve the delivery of these interventions in the future.

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