18 Behavioural Adaptation
Methodological and Measurement Issues

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18.1 INTRODUCTION

A central goal within transportation safety is that travelling and mobility should be as safe and efficient as possible. In an effort to achieve this goal, transportation safety professionals often focus on developing safety systems (e.g., road safety countermeasures) centred on the vehicle or the environment with the expectation that drivers will learn to interact with and adapt to the newly developed safety systems in ways that are consistent with their intended goals. However, drivers have a remarkable ability to adapt to safety systems in ways that are unanticipated by those who develop the safety systems; this adaptation can serve to meet the needs of the driver but be counterproductive to safety and efficiency. Within this chapter and book, these unanticipated changes are generally referred to as behavioural adaptations.

In the past 30 years, there has been an increased focus on examining and understanding behavioural adaptation from a theoretical perspective (see Brown and Noy, 2004; Fuller, 1984; Wilde, 1982; and Section II of this book) and from a more practical perspective in terms of behavioural adaptations relative to the use of vehicle and infrastructure-based safety systems (see Section III of this book). However, despite this increased focus, there has been no published work examining the experimental issues that arise from behavioural adaptation research. This chapter will focus on several methodological, measurement, and analysis issues to be considered when designing, conducting, and evaluating studies that examine behavioural adaptation. This chapter is divided into two sections. The first, methodology issues, will discuss characteristics of behavioural adaptation that should be considered within the context of evaluations that purport to examine driving behaviour and subsequent behavioural adaptations. This section will also discuss several issues relative to evaluation design and will summarize significant experimental confounds that are specific to behavioural adaptation research. The second section, measurement and analysis issues, will discuss the use of several statistical procedures that can be employed in behavioural adaptation research. This chapter will provide a practical foundation that will facilitate researchers' ability to design and conduct adequate evaluations of behavioural adaptation and will facilitate stakeholders' (e.g., researchers, product developers, legislative agencies) ability to interpret and employ the results in the development of effective safety systems or transportation safety policy.

18.2 METHODOLOGY

18.2.1 What Characteristics of Behavioural Adaptation Need to Be Considered When Addressing Methodology and Measurement Issues?

The generally accepted definition of behavioural adaptation was forwarded by the Organization for Economic Cooperation and Development in 1990 (OECD, 1990) and states that behavioural adaptation is the collection of 'behaviours which may occur following the introduction of changes to the road–vehicle–user system and which were not intended by the initiators of the change' (p. 23). While a full assessment of this definition is beyond the scope of this chapter (see Chapter 2 for an assessment), it is important to note that this relatively straightforward definition betrays the true underlying complexity of behavioural adaptation. Behavioural adaptation can manifest itself in a number of ways that make it challenging for researchers to identify measures that appropriately reflect the unintended changes that occur in task performance. To identify behaviours that may be indicative of behavioural adaptation we must determine what specific behaviours to measure. A poor selection of measures could lead to misleading results that indicate no behavioural adaptation when adaptation indeed occurred; this would be a detriment to effective decision making among road safety stakeholders and authorities.

The identification of several primary characteristics of behavioural adaptation provides guidance for the design of studies and the selection and evaluation of measures indicative of behavioural adaptation. A central characteristic of behavioural adaptation is the 'behaviour type' exhibited by drivers' response, and potentially other road users, to a change in a safety system. A behaviour type represents a specific driving task type (e.g., moving foot to the brake), how that task is performed (e.g., risky braking), and at what level of driving control (i.e., operational, tactical, or strategic). When considering the quantification, evaluation, and selection of measures to identify behavioural adaptation, each task associated with driving (or road user's task) must be identified so that any changes based on exposure to a safety system is captured separately from the level of control and motivational factors. The choice of analysis can then guide the understanding of how performance may change over time and why some behaviour types may be more or less likely impacted by the presence of a specific safety system.

18.2.1.1 Behaviour Types

In this chapter, we employ definitions of task types commonly used in the study of human motor learning and control (see Schmidt and Lee, 2005 for an extended description). For example, we put forth the concept that behavioural changes and subsequent adaptation can occur while performing discrete, continuous, and serial behaviours. Discrete behaviours are those that have a definable start and end, and are typically short in duration. An example of a discrete behaviour is moving the foot to engage the brake. When anti-lock brakes were added to vehicles, initial research supported a positive safety benefit of the safety system with the finding that drivers reduced their braking distance significantly in poor weather conditions (Evans and Gerrish, 1996). However, other research that examined performance over longer periods of time found that drivers increased travel speeds (Rompe et al., 1987) and reduced time headways to lead vehicles (Sagberg et al., 1997), potentially reducing a portion of the overall safety benefits of the anti-lock braking system. Drivers were apparently taking advantage of the safety system's benefit to reduce their overall braking distance in safety-critical ways.

A continuous behaviour is one that is characterized by the lack of a definable start and end, such as continuous steering wheel and accelerator pedal inputs while driving. Boyle and Mannering (2004) examined the influence of traffic advisory information on driving speed. Information relative to poor weather conditions such as fog and driving incidents (e.g., snow plow presence) was presented in three treatment conditions that included in-vehicle messages, messages outside the vehicle, and both types of message delivery. In addition, a baseline, no message, condition was included. Results indicated beneficial effects for speed maintenance (a continuous task) when messages were present. However, once drivers were out of the range of the information or if the information was no longer valid, they drove faster, presumably to compensate for the time lost when they were driving slower while receiving messages.

A serial behaviour is a group of discrete behaviours that sequentially make up a larger behaviour. An example of a serial behaviour is changing lanes, which requires a series of discrete behaviours before the lane change manoeuvre is executed: checking the blind spot, activating the turn signal, turning the steering wheel to move the vehicle over into the new lane, and deactivating the turn signal. While there is a possibility that a serial behaviour might be sensitive to behavioural adaptation tendencies, greater insight into behavioural changes are likely achieved by examining discrete behaviours within the larger serial behaviour. For example, the integrated vehicle-based safety system (IVBSS; Sayer et al., 2011) study found that drivers who engaged in more frequent lane changing used their turn signals more when their vehicle was equipped with a lane-change/merge warning and it was turned on compared to when it was turned off. When the system was turned off during baseline driving, drivers were more likely to omit the discrete behaviour of activating the turn signal when completing the overall lane change manoeuvre. The lane-change/merge warning system could be perceived to increase driver risk propensity because drivers were manoeuvring more frequently in traffic and increasing their interactions with other vehicles. However, the increased use of turn signals may actually have offset any negative effects related to driver's adaptation to the lane change/merge warning system. Hence, there is greater benefit in examining discrete behaviours rather than the overall serial behaviour.

The potential for maladaptive changes to occur across the prospective range of discrete and continuous driving behaviours may pose significant challenges to those responsible for designing, conducting, and evaluating safety systems. To ensure internal study validity and generalization of results, careful consideration must be given to the appropriate task behaviours that are indicative of behaviour that is likely to adapt in unintended ways (i.e., the behaviour type). Once changes in task performance are identified and categorized within a particular behaviour type, there is a need to qualify observed changes with respect to their rate of occurrence, how long it takes a change to be observed, and whether the change continues after a safety system is no longer in use.

18.2.1.2 Behaviour Occurrence Rate

Behaviour occurrence rate refers to the frequency that behaviours indicative of adaptation are expected to occur. Specifically, when discrete or continuous behaviours are performed repeatedly, does the adaptation occur every time the behaviour is performed or only during the presence of another factor (e.g., icy roads or heavy traffic)? Behaviour occurrence rate can provide insights into the relative permanence of behavioural adaptation (as a result of brief or prolonged exposure to a safety system). Therefore, it can be a reflection of the transient influence of a safety system or of a more permanent change that results from learning (e.g., motor learning).

Behaviour occurrence rate can provide information on measure selection and evaluation design. Behavioural adaptations that are expected to occur rarely in response to a safety system will require researchers to select measures that are highly sensitive to even a single occurrence. For example, in theory, a safety system may reduce mental workload associated with driving but a driver may only capitalize on this reduced workload by engaging in a secondary task very infrequently. This rule of thumb can be applied to adaptations that are expected to be observed repeatedly but, relative to these adaptations, it will be important to increase the frequency of behavioural observations to better understand the duration of the adaptations over time.

18.2.1.3 Changes in Behaviour over Time

An important characteristic when addressing methodological and measurement issues is the timeframe over which the behavioural adaptation may occur. Similar to behaviour occurrence rate, the timeframe characterizes the relative permanence of behavioural adaptations but does so by examining how long it takes to adapt to a safety system change, how lasting the behavioural adaptations are during safety system exposure, and how transient the effects of behavioural adaptation are after safety system removal. In alignment with human motor learning notions of skill acquisition (Schmidt and Lee, 2005), we can consider adaptation in three stages: immediate, short term, and long term. Immediate refers to adaptation that may occur over a period of time immediately after a driver (or other road user) experiences a change in a safety system. Owing to the relatively short duration of presentation of treatment conditions (e.g., typically 30 min to 1 h), most safety system studies can be categorized into this stage. Fundamentally, these studies examine whether or not a change in behaviour occurs.

Studies that examine how long it may take before adaptation occurs or how long a behavioural adaptation may exist are considered here as short- and long-term studies. The timeframe of these stages is somewhat arbitrary. Short-term studies typically examine the rate at which early behavioural adaptation may occur (see Manser et al., 2010 as an example), which may be on the order of hours, days, or weeks after a change in a safety system, while long-term studies examine the rate of behavioural adaptation over much longer timeframes, such as months or years (see Hjälmdahl and Várhelyi, 2004 as an example). Often, immediate behavioural adaptation is characterized by a significant rate of behaviour change for drivers. Short-term adaptation is typically characterized by a significant but typically lower rate of behaviour change for drivers, while long-term adaptation may be characterized by gradual changes for drivers and, as suggested by Jamson et al. (2010), when considering road safety engineering treatments, investigations should be undertaken to evaluate the 'durability' of treatments and whether the effectiveness for drivers may change over time. Considering these stages is important because some behavioural adaptations may not manifest themselves immediately or may change in nature over time and, if this is expected, the study may have to be extended over time to fully capture the changes.

18.2.1.4 Changes in Behaviour Types after Discontinuation of System Use

The concept of behavioural transfer is most often related to the capacity of general behaviours to continue for a period of time after the use of a safety system is discontinued. Generally, positive, neutral, and negative transfers are determined according to how behaviours carry-over from safety system use to non-use. For example, positive transfer typically reflects the continuation of behaviours after a safety system has been removed from use. Relative to behavioural adaptation, positive transfer would be evident if the period of time after safety system removal exhibited equivalent or increased behavioural adaptations than before the introduction of safety system. In essence, the use of a safety system would contribute to adaptations (the presence of adaptations) even after the system was removed from use (i.e., there would be strong carry-over effects). Theoretically, negative transfer (e.g., dependency) would occur if adaptations after the removal of a safety system were lower than behaviours before a system was introduced. This would suggest the safety system created a dependency that prevented or interfered with the transfer of adaptations to driving after the safety system was removed. Although negative transfer is hypothesized to occur in driving, research efforts have focused on neutral transfer. The terms positive, neutral, and negative refer only to the characteristic and not the qualitative nature of the carry-over effect. For example, positive transfer between safety system use and non-use merely indicates the presence of behavioural adaptation after safety system use is discontinued and does not suggest that adaptations would be beneficial. In fact, most safety system developers hope that their products would promote neutral transfer in that any behavioural adaptations present would dissipate after safety system use has concluded. A depiction of the stages of adaptation and transfer relative to driver support system use is presented in Figure 18.1.

The concepts of positive, neutral, and negative transfer have strong implications for methodological and measurement issues relative to behavioural adaptation. Most safety system designers anticipate that once a safety system is discontinued, driver behaviours will return to levels they were at before the system was introduced. For example, it is assumed that immediately after an adaptive cruise control (ACC) system's headway maintenance control is deactivated, drivers would once again actively

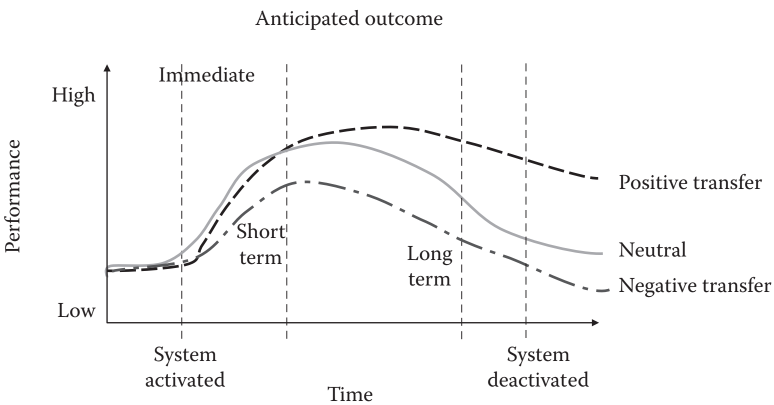

FIGURE 18.1 Schematic depicting the stages of adaptation that may be considered when examining behavioural adaptation relative to safety system use, depicted as performance, as a result of the introduction, continued use, and removal of a safety system.

engage in car following. However, an unanticipated behaviour that may result when transferring from system use to non-use would include complacency in car following because a driver feels the system may still be active. This would be unfortunate as the potential for a crash might increase due to lack of effective headway control. In this example, a critical element of a study of behavioural adaptation would be the inclusion of a transfer condition that compares driver behaviour during and after safety system use. Examinations of behavioural adaptations that are expected to manifest themselves over time, to endure or change over time, or to change due to safety system discontinuation would likely benefit from the inclusion of timeframe as an experimental methodology factor.

18.2.2 Primary Methodological Issues

18.2.2.1 Selection of Dependent Variables

While it is beyond the scope of this chapter to address all relevant methodological issues, this section discusses those that are particularly important to behavioural adaptation studies because of their marked influence on study validity and subsequent generalization of results. One of the issues that may be most important to researchers is the selection of dependent variables that may be sensitive to and indicative of behavioural adaptation. While the decision to employ particular behavioural adaptation variables must be directed by the nature of the research questions, there is not one defined method by which to select the most appropriate variables. In fact, the many different sources and manifestations of behavioural adaptation can create challenges when trying to identify which set of dependent variables is best. Fortunately, some research examples can provide tentative direction in variable selection, such as work that has shown how cognitive and visually demanding tasks can influence driving performance in divergent ways. For example, Engström et al. (2005) found that visual demand resulted in reduced speeds and increased lane keeping variability whereas cognitive demand had no affect on speed and resulted in reduced variability in lane keeping in motorway driving. The general implication is that the type of safety system being evaluated and how it is expected to influence behaviour should direct the selection of driver behavioural adaptation-dependent variables. Based on the cited example, if a safety system imposes an extra visual load on the driver via an in-vehicle interface, then the inclusion of lane keeping or speed maintenance variables would be relevant to the study. However, we acknowledge that the range of variables related to behavioural adaptation is still being examined and that it may not always be possible to predict what behaviours will occur. This may suggest that researchers should examine as many variables as possible; however, this is not a prudent approach because statistically controlling for an increased number of comparisons make true differences difficult to identify. We submit that a focused effort by researchers will identify the majority of variables that would be indicative of behavioural adaptation.

Research has shown that cognitive or visual tasks that are unrelated to the primary task of driving (e.g., lateral and longitudinal vehicle control) may also be influenced by system use. Manser et al. (2005) investigated changes in vehicle controllability when assisted by a driver support system that consisted of a haptic accelerator pedal with continuous information to drivers about the criticality of objects in the path of the participant's vehicle (see Manser et al., 2004 for a full system description). The authors suggest that cognitive effort, although not measured directly, was reduced as a result of the driver support system and vehicle controllability improved, suggesting that resources were reinvested into the primary driving task. However, productivity of the cognitively demanding in-vehicle secondary task also improved suggesting that drivers were reinvesting some of the spare effort into a task not related to the primary task of vehicle controllability (see also Rudin-Brown and Parker, 2004). Thus, behavioural adaptation in this example occurred in a secondary task unrelated to the primary task of driving, which the system was designed to support. Examining primary driving performance in isolation would not have revealed the reallocation of attention to this non-driving-related task when the system was active, which could negatively affect overall driver safety. On the other hand, a recent field operational test of a suite of integrated collision avoidance systems demonstrated that drivers did not engage in more non-driving-related secondary tasks when the systems were active (Sayer et al., 2011), suggesting that, in this case, there was no behavioural adaptation to the presence of the technology with respect to non-driving tasks during the 28-day testing phase. The differences in results between these studies may have been due to motivational factors (e.g., being forced/instructed to complete a task versus self-selecting to complete a task in a natural environment) that varied as a consequence of testing conditions (e.g., simulator study vs. field operational test). Collectively, these research examples suggest the need to select behaviour variables that are associated with anticipated changes in behaviours or associated with the underlying constructs that may be influenced by safety system use. In addition, precedent should drive the selection of variables such that foundational work conducted in simulated environments can inform the identification of variables to be examined in on-road research.

18.2.2.2 Selection of Independent Variables

A second methodological issue that can significantly influence the validity and generalizability of behavioural adaptation studies is the selection and use of control groups and independent variables. A control group typically entails observations of driver behaviours that were not exposed to the system intervention (or treatment). A comparison is made between a control group and treatment group to determine if the treatment had any effect. In many cases, a participant's own behaviours before, during, and even after treatment are compared. This control-treatment-control arrangement is typically referred to as a within-subjects design because each driver experiences all control and treatment conditions. In contrast, the behaviours of two (or more) groups of participants, one receiving treatment and one not receiving treatment, can be compared against each other in what is termed a between-subjects comparison. Within-subjects comparisons can be quite useful because they typically require fewer participants while allowing higher statistical power, whereas a between-subjects design will likely require more participants to attain similar statistical power. However, the choice to use a within- or between-subjects design should not be dictated by the availability of participants but rather by the selection of the experimental design that would provide the greatest insight into behavioural adaptation.

A significant advantage of employing a between-subjects design is that the confounds associated with within-subjects design can be addressed, thus allowing researchers to identify changes in behaviour that are truly representative of safety system use. For example, through the use of a between-subjects control group, the influence of maturation on driving behaviours in young drivers could be identified and statistically removed when examining long-term behavioural adaptation to a driver support system. In addition, a between-subjects experimental design can be useful for reducing learning/practice effects as a result of prior experience with testing.

18.2.2.3 Time Period

The period of time over which a study is conducted must be adequate to identify behavioural adaptation. As indicated earlier, behavioural adaptation can manifest itself over different timeframes depending on the behaviour type and behaviour occurrence rate. Hence, researchers should consider selecting study timeframes that will reveal the complete extent and nature of behavioural adaptation over anticipated durations. Employing a methodology that examines short-term behavioural changes to a driver support system, for example, may provide evidence of initial adaptation but it will fail to indicate how drivers may continue to adapt to the safety system over longer periods of time or whether behavioural adaptation asymptotes with time. In contrast, employing a long-term methodology to examine short-term adaptations would not be a good use of experimental and financial resources. Currently, there is no standard or recognized acceptable method that may provide timeline selection guidance. Researchers must consider factors such as the anticipated duration of system use, potential behaviour occurrence rate, and results of allied behavioural adaptation studies. The selection of an appropriate methodology timeframe is certainly dictated by the expected duration of behavioural adaptation or, if the expected duration is unknown, one or more short duration studies will be warranted to better determine if longer-term methodologies are necessary.

18.2.2.4 Testing Environment

Studies of behavioural adaptation in response to a change in safety systems have been conducted in a variety of testing environments including driving simulators (e.g., Horberry et al., 2006; Lewis-Evans and Charlton, 2006; Manser et al., 2010), controlled on-road environments such as closed course test tracks (e.g., Rudin-Brown and Parker, 2004), and normal driving environments using participants' own vehicles (e.g., Hjälmdahl and Várhelyi, 2004). The selection of testing environment when examining behavioural adaptation is a methodological consideration that is dictated by a variety of factors. Two of these factors, system development stage and resources, appear to have a greater impact on the selection of testing environment compared to other factors, such as the actual type of safety system being tested and behaviours to be examined. System development stage refers to the degree to which a particular safety system has been developed on a continuum that ranges from concept identification to product deployment. The use of driving simulators may be warranted when examining safety systems that are in the conceptual or early prototype stages because of their ability to quickly and inexpensively evaluate proof of concept safety systems such as collision warning systems (see Manser, 2010 for a review). As a safety system evolves from a prototype to a deployable product, it may be necessary to conduct behavioural adaptation studies in more natural driving environments to expose drivers (and to some extent the safety system) to a greater number of naturally occurring factors that may impact system use. However, an inherent challenge in the conduct of increasingly naturalistic studies relates to the need for additional resources. These studies require significantly more human effort to develop safety plans, testing equipment, and safety system development, which, in turn, results in studies that are significantly more costly to conduct than simulator-based studies. Given that cost is often a factor that must be considered when conducting behavioural adaptation studies, the use of testing environment will continue to be a prominent methodological consideration.

Finally, we forward the notion that the choice of methodology to address behavioural adaptation issues must be guided by the nature of the driving task, expected and unexpected behavioural changes (to the extent that one can predict unexpected changes), the underlying theory being used to make predictions of about behavioural adaptation, and, of course, the research question of interest. After a critical examination of these items, researchers can then address the array of methodological considerations listed above.

18.2.3 Potential Confounds Inherent to Behavioural Adaptation Research

The success of an investigation of adaptation to a safety system can be influenced significantly by confounding factors. Confounding factors are extraneous elements of a study that are not or cannot be controlled (e.g., age and experience), but can unduly influence (e.g., bias) the variables under investigation. Identifying and controlling for confounding factors is crucial for maintaining a study's internal validity so that results can be attributed to the correct variable. Practically, the identification and control of confounding factors will ensure that the nature and magnitude of behavioural adaptation can be understood with certainty and that these findings can be applied to the development of safety systems to avoid behavioural adaptations. This section identifies several prominent experimental confounds most relevant to behavioural adaptation studies along with methods to address them.

18.2.3.1 Behavioural Adaptation versus Skill Learning

The ability to adapt to situations is a fundamental characteristic of human beings that can result from behavioural adaptation or from the natural process of learning to perform a task. When designing or evaluating a study it is important to differentiate between changes in behaviour (or performance) that are due to behavioural adaptation, which reflect a change in the underlying cognitive or behavioural processes, versus those that are due to skill or task learning alone over time. Changes in behaviour throughout a study that are due to skill learning may be attributed incorrectly to behavioural adaptation. This situation, which can lead to the false finding that behavioural adaptation may exist when in fact it does not, may convince developers to reject the deployment of safety systems that actually facilitate performance and safety. This exact situation was addressed by Manser et al. (2005) who examined the trade-offs between vehicle controllability and in-vehicle secondary task productivity when drivers were presented with a haptic accelerator pedal that provided information about the criticality of objects in their path. The in-vehicle secondary task, which was the primary indicator (i.e., dependent measure) of behavioural adaptation, consisted of a visual–cognitive–manual arrow selection task. However, given that drivers found this task to be quite demanding in its own right, it was necessary to ensure that they did not continue to learn the in-vehicle secondary task during the study. To address learning, drivers received a lengthy practice session with the arrow task prior to the beginning of the study. The researchers also examined changes in in-vehicle secondary task productivity between the first and second halves of the baseline and treatment conditions, respectively. Their results indicated that in-vehicle secondary task productivity did not improve within the baseline or the treatment conditions but did improve *between* the conditions, thus indicating no learning effect but instead a treatment effect. As indicated in this example, researchers must address the potential influence of learning so that study results can be properly attributed to the treatment condition.

18.2.3.2 Experimental Artefacts

A second significant confound that can occur when examining behavioural adaptation, or with any experimental study for that matter, is the influence of experimental artefacts. Similar to skill learning, experimental artefacts may result in changes in driving behaviour that could be wrongfully interpreted as behavioural adaptation or they may serve to attenuate the effects of behavioural adaptation. Examples would include continued adaptation to a driving simulator during an experiment, adaptation to an on-road test vehicle, and seasonal/weather effects (e.g., snowy conditions in winter) over long periods that might influence driving style. These confounds can be easily addressed by proper use of control groups, counterbalancing, and randomizing participants across potential confounds. For example, for studies conducted over long periods in which seasons may influence performance (i.e., driving in snowy winter conditions may prompt more cautious driving compared to summer conditions), it will be necessary to counterbalance study participants across each of the four seasons (e.g., 25% of study participants in a 1-year study begin in each of the four seasons). Other confounding variables such as boredom and participants' desire to finish a study can be much more difficult to identify and control. However, steps to address these confounds must be instituted so that the true effects of behavioural adaptation can be identified. For example, Manser et al. (2010) examined changes in gap acceptance and rejection behaviours in response to the introduction, use, and discontinuation of use of an in-vehicle intersection decision support system. The experiment was conducted in a driving simulator for 1 h each day using multiple intersection crossing trials over a 1-week period. Prior to the study, the authors anticipated that boredom due to repeated simulator exposure might serve as an experimental confound because participants may try to complete the study quickly to relieve boredom instead of performing the task at a normal pace as they would in the real world. Questionnaires were employed, therefore, to assess boredom given that no standardized test exists to measure this construct. While no behavioural adaptations were identified (in fact, positive results increased over time) some participants indicated via the questionnaires that they were indeed bored near the end of the study. As a result, it may be assumed that at least some changes in performance might have been due to boredom. The presence of experimental artefacts is a serious issue to be addressed by researchers due to its ability to negatively impact internal and external study validity.

18.2.3.3 External Confounds

Factors that are not associated with the experimental design itself may also serve to confound studies that examine behavioural adaptation. One prominent external confound that can be directly manipulated by researchers for studies examining long-term behaviours is participant payment schemes. Participant perceptions of reasonable reimbursement may serve to influence behaviours or attitudes while using a new safety system. A perceived conservative reimbursement scheme may result in non-compliant or under-motivated behaviours while a liberal reimbursement scheme may result in participants trying 'too hard' to complete the study as the researcher might like. Our general experience is that older participants often feel participant reimbursements are too liberal and, as a result, they generally indicate that they 'try hard' to perform well in a study. A second external confound, and one that is often not under direct control of a researcher, relates to evaluation resources. We mentioned previously that resources (e.g., financial and staffing) were a significant methodological consideration when conducting studies in test track and on-road environments, but they are also a potential confound in that a limited supply of resources may constrain the necessary scope of a behavioural adaptation study. For example, limited study funding can constrain the number and type of independent variables (e.g., iterations of system design, participant age groups) and dependent variables (e.g., inability to examine the full array of driver behaviours or cognitive processes that are indicative of behavioural adaptation) that can be included in a research study. The subsequent utility of results may, therefore, also be limited. This is not to say that all behavioural adaptation studies (in particular test track and on-road studies) require significant resources but instead suggests that researchers need to carefully balance available resources with project goals, potential application of results, and sponsor expectations. For example, it is generally recognized that the closer a novel safety system is to deployment the more advantageous it is to conduct on-road controlled studies because they will more appropriately replicate the demands of typical driving and be more likely to uncover the true extent of any behavioural adaptation. When resources are limited, it is the responsibility of the researcher to indicate any study limitations or limitations of any results to a study sponsor. Failure to do so may result in the conduct of a study that has limited validity and value.

18.3 MEASUREMENT

The first half of this chapter characterized behaviour types that can be examined to identify behavioural adaptation, as well as methodological issues that can arise in studies on behavioural adaptation. This next section addresses measurement and analysis issues that can influence the identification of behavioural adaptation. Equally important to selecting measures and specifying a time period and experimental location for a study is the level of detail that the data needs to be examined. For example, traditional analysis of variance (ANOVA) techniques where data is aggregated to a treatment level may not always be adequate to observe changes at varying time periods but may be useful in examining effects in the immediate adaptation stage (i.e., before and after system change). In fact, any significant differences may no longer be observed at the aggregated treatment level because the driver has already learned to adapt to the changing environment within the treatment period. That is, the overall trip outcome may demonstrate similar mean speed or standard deviation of lane positions but in fact, there were changes within the treatment (or condition) that have been washed out. For example, in a study by Boyle and Mannering (2004), the travelling speed across a stretch of road did not seem to change regardless of the advisory system provided to the driver. However, when the road segments were examined across a series of shorter segments, the difference in speed became more obvious. In fact, the drivers were slowing down when informed to do so (as anticipated), but would then immediately speed up, going faster than they would normally, to make up the time they lost from slowing down in an earlier segment.

To examine the changes that can occur over different time periods (e.g., minutes, hours, days), other statistical techniques that account for non-linear changes, differences in driver populations, and changing patterns of behaviour can be used. Applying these statistical techniques requires an understanding of their usefulness as well as the type of information to be gathered beforehand.

18.3.1 Capturing Exposure and Adaptation

It is important to ensure that some measure of exposure (e.g., time, distance) can be collected for quantifying behavioural adaptation. Exposure can be quantified in terms of 'exposure to the system or change' as well as 'exposure during the length of the study or observation period'. It can be estimated as a magnitude, frequency, or duration. Within the driving domain, exposure can be measured in terms of time and distance driven, relative change in time and distance across different time periods, conditions, or task types, and frequency of engagement in safety system or secondary tasks.

Adaptation can be quantified in terms of the magnitude of change immediately after a system change occurs (immediate adaptation) and over a prolonged use period (long-term adaptation). Researchers have shown that behavioural adaptation is not merely the perception of risk, but encompasses other behaviour types related to motivation (Rothengatter, 2002), purpose, and driving style (Hoedemaeker and Brookhuis, 1998). Commercial vehicle drivers may slow down during adverse weather conditions, but may change sleeping routine to adapt and compensate for the miles lost by driving during times when they were originally supposed to be resting. Thus, different combinations of behaviour types and environmental conditions may lead people to adapt inappropriately (Evans, 1991). This section describes cluster analytic techniques, which are useful for revealing subgroups of drivers that differ on motivational factors, while functional data analysis (FDA) can be used to observe drivers' performance over time. Drivers' adaptive behaviour based on changes in the system can then be examined based on these individual differences using structural equation or auto-regressive modelling techniques.

18.3.2 Analytical Tools

There exist many analytical tools capable of capturing adaptive behaviour. These tools are used after data has been collected on a safety system and after descriptive statistics have been examined. Descriptive statistics provide a means of understanding (mean, median, standard deviation, frequency) and visualizing the data (scatterplots, box plots, histograms, pie charts) before any inferential statistics are conducted. For examining behavioural adaptation, plots of the dependent variables over time are very useful. This section describes a selection of these inferential techniques, used previously in the driving domain to provide insights on how behaviour changes over time and space. It is important to note that these are not the only techniques nor should an analyst be restricted to these tools.

18.3.2.1 Cluster Analysis

Cluster analysis is an exploratory data analysis tool for solving classification problems (Lattin et al., 2003) and provides a means for classifying drivers into groups based on their responses to behavioural questions (e.g., driving style questionnaire, sensation seeking, acceptance). It is useful in revealing more homogeneous groups of drivers based on their motivation, driving styles, and driving purpose, all of which can influence driver behavioural adaptation. These constructs can be gathered from survey instruments that are typically used in conjunction with the performance data (collected from simulator, test track, on-road, or naturalistically). The participants' cumulative responses then provide insights on why a change may lead to a positive or negative safety consequence with greater exposure.

Cluster analysis has been used in previous studies to classify drivers' propensity to change behaviour based on perceived value of information (Conquest et al., 1993), driving purpose (Ng et al., 1998), trust in a system (Dickie and Boyle, 2009), and driving style (Xiong et al., 2012). As an example, Dickie and Boyle (2009) conducted a study on the use of ACC and observed three cluster groups based on survey responses to questions related to their knowledge of the ACC system in their personal vehicle. The three groups centred on those who were aware, those who were unaware, and those who were unsure of ACC limitations. Further examination revealed that drivers who were unaware or unsure exhibited potentially more unsafe behaviour than the drivers in the aware group. This can have implications with prolonged ACC use.

There are many different clustering procedures and they typically fall into two categories: hierarchical (such as complete linkage, single linkage, Ward's method), and non-hierarchical (such as *k*-means clustering). The proper selection is dependent on the type of data being clustered (nominal, ordinal, ratio, or scaled data). Once subgroups of drivers are revealed, these groupings can then be included in the analysis as an independent or explanatory variable that can then provide some additional insights on differences observed in adaptation strategies (Chorlton and Conner, 2012; Ouellette and Wood, 1998).

18.3.2.2 Auto-Regressive Time-Series Models

The expression of behavioural adaptation may depend on inherent time dependencies that should be considered in any analysis. Time-series modelling can use outcomes based on behaviour occurrence rates to capture whether the adaptation will be fleeting or will persist over long periods. Data that is time dependent can be examined using several techniques including moving averages, exponential smoothing, autoregressive moving average models (ARMAs), and distributed lags analysis (Kendall, 1990). Frequency domain methods (e.g., Fourier and fast Fourier transforms) can also be used to examine time-dependent outcomes.

When conducting a time-series analysis, researchers will need to demonstrate an understanding of the underlying patterns (e.g., trends, serial correlation, seasonal effects, and the residuals). Findings that do not appropriately account for these patterns may have confounding effects leading to inappropriate conclusions. An example of the details that need to be considered is presented here in the context of an ARIMA (auto-regressive integrated moving average) modelling approach. An ARIMA model can be used if the data show three major features: (1) auto-regressive, (2) moving average, and (3) integrated. The analysis needs to first identify what anticipated trends and cyclical effects are likely in the data. A time-series plot of anticipated events (e.g., number of text messages, cell phone calls, or even lane departures) is often helpful. As an example, Figure 18.2 is a plot of events over consecutive time periods. An analyst may examine the means before and after system activation and not observe any significant differences. However, upon further examination, this would not be appropriate given the existence of serial dependence (values of adjacent members of a time series are correlated) and that the data are nonstationary (i.e., any variations observed are not due to randomness only and as such, the mean and variance is not actually constant over time). There also appears to be a cyclical (or seasonal) pattern that needs to be accounted for.

There will always be some random variation in the data. However, the value of time-series modelling is that it is possible to do some data smoothing (i.e., clean up the noise in the data) so that patterns or trends in behaviour can be more readily observed. Two common techniques for smoothing data are moving averages and

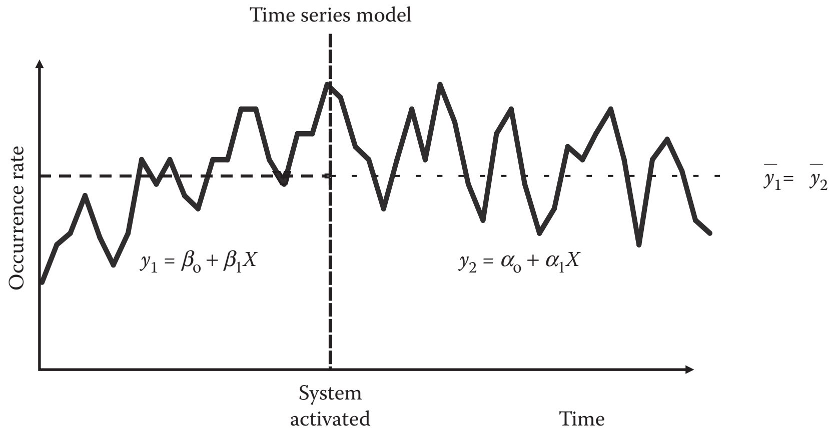

FIGURE 18.2 Change in occurrence rate over time.

exponential smoothing. With moving averages, each period of interest is based on an average of the observations across a moving span (or window) of multiple observations. Moving averages can be calculated on any number of data points. For example, the moving average window might just be the current observation and the previous observation, or, the window could include the current observation and the previous five observations. Larger windows (or more aggregated data) result in smoother lines but contain less detail.

The auto-regressive component represents the lingering effects of previous observations and is accounted for in a time-series model by including the previous time period. In other words, the model is regressing on previous observations (or regressing onto itself). Like the moving average component, the auto-regressive (AR) component can have different orders. A model that uses only the previous time period is a first-order model, whereas a model that includes the previous two time periods is a second-order model. The number of past time periods to include in the model is based on the auto-correlation that exists between the current observations and past observations. Adaptive behaviour may also exhibit cyclical or seasonal trends (i.e., changes observed during commute hours only, on weekends, or in summer months) and this effect (consecutive lag) can be accounted for by including the range of lag in the model (differencing the data).

When each of these components is accounted for in the model, then a stationary time-series model is obtained and the outcome (or dependent variable) can now be treated like a normal distribution. In other words, the mean, variances, and correlations would no longer (for analysis purposes) change over the time sequence and any trends reported would be statistically meaningful and could also be used for future descriptors. The overall fit of the model can also be improved with the addition of other known explanatory factors that can account for intervention effects, and other time-dependent covariates.

18.3.3 Structural Equations

Structural equation models can be used to examine behavioural adaptation due to situation, system, or environmental changes. Structural equations or simultaneous equations represent systems of equations with two or more unknown variables that are related to each other through an equal number of equations. An example of a simultaneous equation is the three-stage least-squares (3SLS) technique used in the earlier-cited study by Boyle and Mannering (2004) to model changes in speeds. However, this same technique can be used to examine changes in time and route choice behaviour (e.g., alternate routes, freeway versus highway) given various driving situations. These equations use a time-dependent multi-stage approach that can capture small changes within a driver. As an example, the impact of speed (both mean and standard deviation) from one time period to the next (or previous time period) can be written as a system of equation as follows:

$$\begin{aligned} \mathtt{m} &= \mathtt{b}_1 + \mathtt{a}_1\mathbf{X}_1 + \mathtt{f}_1\mathtt{s} + \mathtt{e}_1 \\ \mathtt{s} &= \mathtt{b}_2 + \mathtt{a}_2\mathbf{X}_2 + \mathtt{f}_2\mathtt{m} + \mathtt{e}_2 \end{aligned} \tag{18.1}$$

where μ is the mean speed for each driver in a (for example) 1 km segment and σ is the standard deviation of the speed over the segment. This equation indicates that speed in one time period is used to predict the speed in the next period. Driving inherently requires changes in speed behaviour and thus, how fast a driver is going in one time period is highly dependent on how fast he or she was travelling in the previous time period. In this model, mean speed and standard deviation of speed are interrelated endogenous variables (i.e., they are correlated and highly dependent on the state of the system), while $\mathbf{X}_1$ and $\mathbf{X}_2$ are vectors of roadway, environmental, traffic, and driver characteristics. The estimated model coefficients are represented by the variables β_1, β_2, φ_1, and φ_2 as estimable scalars, and α_1 and α_2 as estimable vectors. The residuals, ε_1 and ε_2, are normally distributed.

Because ordinary least-squares estimation of this equation system will produce biased and inconsistent coefficient estimates due to correlation between endogenous right-side variables (i.e., mean speed and standard deviation of speed) and the equation's disturbance term (Geraci, 1987; Greene, 1993), this simultaneous set of equations can be used instead to account for this bias and inconsistency. The 3SLS estimation procedure calculates instruments for endogenous variables (mean speed and speed deviation) by regressing against all exogenous variables (e.g., roadway, environment). These instruments are then regressed to estimate the variance–covariance matrix of disturbances (i.e., the relationship between ε_1 and ε_2). Using this matrix, generalized least-squares (GLS) are then applied to estimate the model coefficients.

18.3.4 Functional Data Analysis

In a traditional linear regression model, performance is examined at a cross section in time, or otherwise, aggregated to some level. The benefit of the FDA is that the performance does not need to be aggregated or examined merely at one time point. Rather, the technique allows one to examine the function of observations over some time period or space interval (Faraway, 1997).

FDA is a multi-step process in which the existing data is converted to a functional form, smoothed using Fourier functions or B-spline functions, and then modelled using a functional one-way ANOVA (fANOVA). In other words, FDA uses information along curves (or functions). This technique is therefore useful to examine adaptive behaviour that clearly changes over space and time (Figure 18.3). This differs from the time-series analysis previously described, in that a FDA does not require equally spaced time intervals.

Within the driving domain, Chaffin et al. (2000) have used this modelling technique to examine reach motion posture, and the same principle applies when examining driver behaviour. Because behaviour is measured over time, this model can be used to examine the changes as a driver gains exposure to a safety system, and is also useful for examining difference prior to and after the implementation of the safety system. Models can also be developed to account for various responses, including changes in braking patterns, acceleration, steering, and speed. In summary, FDA can help show the performance profiles as drivers adapt to various safety systems.

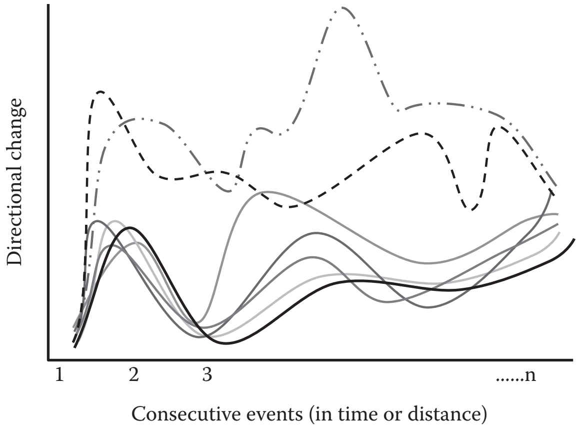

FIGURE 18.3 Example of curved data used for functional data analysis.

18.4 CONCLUSIONS

As with general experimental methods, those methods of evaluation, measurement, and analysis relevant to behavioural adaptation research should be appropriate to the research hypothesis and must have sufficient sensitivity to identify changes in behaviour (i.e., those behaviours that are not anticipated by system designers) in response to changes in road traffic systems. Failure to employ appropriate evaluation design and analysis methods may result in false findings that indicate no behavioural adaptation exists when it does (i.e., Type II error) or that behavioural adaptation exists when in fact it is not present (i.e., Type I error). Either type of error that occurs with regard to a set of findings will misinform stakeholders (e.g., researchers, road traffic system developers, policy-makers) at the very least and could lead to the development and promotion of road traffic systems that are detrimental to driving behaviours and safety. To avert this situation, researchers must understand the characteristics of behavioural adaptation, address methodological considerations and potential confounding factors, and select an appropriate data analysis strategy. Addressing these elements can result in the conduct of studies that have significant value for the research community, stakeholders, and, most importantly, for the general public who will use these newly developed road, traffic, and vehicle systems.

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