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Aggressive Driving Behaviors and Immediate Auditory Feedback: A Study in the Wild

Comportamientos de manejo agresivo y retroalimentación auditiva inmediata: Un estudio en condiciones reales

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Abstract

Aggressive driving patterns represent a critical factor in traffic accidents worldwide. This study examines the effectiveness of immediate auditory feedback on aggressive behaviors. We conducted an in-the-wild study with eight drivers, monitoring harsh acceleration, aggressive braking, and speeding events during a complete driving day using mobile devices. Results show 37% reductions in total aggressive events per km and 70% in harsh braking events for the experimental group, with large effect sizes (Cohen's d = -1.424 for braking, d = -0.745 for total events). These substantial effect sizes, combined with high user acceptance (M≥6.25/7), provide preliminary evidence that immediate auditory feedback is a promising intervention strategy for reducing aggressive driving behaviors, particularly conscious maneuvers requiring deliberate cognitive processing, such as harsh braking. Findings establish effect magnitude estimates essential for designing adequately powered confirmatory studies (N≥30 per group) and demonstrate technical feasibility and user acceptance necessary for large-scale field implementations.

Keywords: Aggressive driving; vehicle monitoring; GPS; smartphone; auditory feedback; road safety

Resumen

Los patrones de manejo agresivo representan un factor crítico en los accidentes de tráfico a nivel mundial. Este trabajo estudia la efectividad de la retroalimentación auditiva inmediata sobre comportamientos agresivos al volante. Se llevó a cabo un estudio en condiciones reales con ocho conductores, monitoreando eventos de aceleración brusca, frenado agresivo y exceso de velocidad durante una jornada completa de conducción mediante dispositivos móviles. Los resultados muestran reducciones del 37% en eventos agresivos totales por kilómetro y del 70% en eventos de frenado brusco en el grupo experimental, con tamaños de efecto grandes (d de Cohen = −1.424 para frenado, d = −0.745 para eventos totales). Estos tamaños de efecto sustanciales, combinados con alta aceptación por parte de los usuarios (M≥6.25/7), proporcionan evidencia preliminar de que la retroalimentación auditiva inmediata representa una estrategia de intervención prometedora para reducir comportamientos de manejo agresivo, en particular maniobras conscientes que requieren procesamiento cognitivo deliberado, como el frenado brusco. Los hallazgos establecen estimaciones de magnitud del efecto esenciales para diseñar estudios confirmatorios con potencia estadística adecuada (N≥30 por grupo) y demuestran la viabilidad técnica y aceptación de usuario necesarias para implementaciones a gran escala en campo.

Palabras clave: Manejo agresivo; monitoreo vehicular; GPS; teléfono inteligente; retroalimentación auditiva; seguridad vial

1 Introduction

Aggressive driving represents one of the main risk factors in traffic accidents, contributing significantly to road mortality worldwide (Arvin et al., 2019), (Mantouka et al., 2019) . Aggressive behaviors behind the wheel, such as harsh acceleration, aggressive braking, violent turns, and speeding, significantly increase the risk of collisions and compromise the safety of drivers and other road users. Despite awareness campaigns and strict regulations, these behaviors persist as a critical challenge for road safety (World Health Organization [WHO], 2023), (Phillips et al., 2011).

Advances in mobile technologies and Global Positioning Systems (GPS) have created new opportunities to detect and modify these risky behaviors in real-time. Modern smartphones, equipped with accelerometers, gyroscopes, and processing capacity, can achieve accuracies up to 96-99% in detecting aggressive maneuvers (Mantouka et al., 2021), comparable to professional OBD-II systems. However, solely detecting these behaviors does not necessarily mean that drivers will reduce them. Effective intervention mechanisms are required to influence drivers' behavior and reduce risky maneuvers.

Various feedback strategies exist for intervening when risky behaviors are detected. Immediate auditory feedback is a promising intervention strategy based on operant conditioning principles, in which auditory signals act as aversive stimuli to reduce the frequency of undesirable behaviors (Mohd Zaki et al., 2021). From the perspective of persuasive technology, immediate feedback acts as a prompt that, according to Fogg's Behavior Model (Fogg, 2003), (Fogg, 2009), can effectively modify behavior when it converges with motivation (safety) and ability (vehicle control). Unlike delayed interventions that provide weekly or monthly reports (Ebert et al., 2025), immediate feedback allows for a direct association between behavior and consequence, enhancing its effectiveness by eliminating the cognitive load of remembering and associating past events.

We refer to immediate auditory feedback as feedback received by the driver with low latency (less than three seconds). Despite the theoretical potential of immediate auditory feedback, a significant gap exists in the literature. While previous studies have evaluated delayed feedback with latencies of days or weeks (Ebert et al., 2025) or have focused exclusively on algorithmic detection accuracy without measuring behavioral changes (Z. Chen et al., 2015), (White et al., 2011), studies evaluating the impact of immediate auditory feedback on aggressive driving behaviors under real-life driving conditions are essentially nonexistent. This distinction is critical: laboratory or simulation studies offer rigorous experimental control but lack ecological validity, while in-the-wild evaluations capture the real variability of driving behavior, including different road types, variable traffic density, changing weather conditions, and the natural fatigue that a driver experiences during their day, factors that are impossible to replicate in controlled environments fully.

The central hypothesis of this work is that drivers exposed to immediate auditory feedback will exhibit a lower frequency of aggressive events over a full day than drivers who receive no feedback. Based on dual-process theory (Kahneman, 2011), (McKenna, 2016) , which distinguishes between automatic, fast cognitive processes and deliberate, analytical ones, it is anticipated that auditory feedback will demonstrate greater effectiveness for conscious and intentional behaviors (such as harsh braking, which requires active attention and decision-making) in contrast to more automated behaviors (such as routine acceleration, which is executed with minimal conscious control). This prediction is supported by evidence that behaviors requiring greater active cognitive processing are more susceptible to modification through immediate external signals (Engström et al., 2017), (Brown et al., 1969).

This work addresses the following research questions:

RQ1: Do drivers exposed to immediate auditory feedback demonstrate a lower frequency of aggressive driving events per kilometer during a complete driving day compared to drivers who receive no feedback?

RQ2: Does immediate auditory feedback show differential effectiveness for conscious versus automated driving behaviors, specifically demonstrating greater reductions in harsh braking (deliberate, System 2 behavior) compared to harsh acceleration (automated, System 1 behavior)?

RQ3: Do participants in the feedback group report higher system acceptance levels and greater awareness of their driving behavior compared to the control group?

To address these questions, a between-subjects experimental design was employed to avoid carryover effects (feedback-induced awareness persisting into no-feedback conditions), enhance ecological validity (mirroring real-world deployment where drivers either have systems or do not), and minimize participant burden within a single-day protocol. While this design requires larger samples to achieve statistical power compared to within-subjects approaches, it provides the cleanest test of immediate feedback effects. The study included eight non-professional drivers (four with immediate auditory feedback, four as controls without feedback) during a full driving day (8-10 hours) under natural conditions. The hybrid GPS-smartphone system continuously monitored aggressive driving events, providing instantaneous auditory alerts to the experimental group at the exact moment each event was detected. The findings help fill the identified gap by providing empirical evidence on the effectiveness of immediate auditory feedback in real scenarios, combining precise detection with instantaneous intervention to evaluate the effects of operant conditioning on the frequency of aggressive events.

2 Related Work

2.1 Vehicle Location Platforms

This section presents some previous work in this area. Salim and Idrees (Salim & Idrees, 2013) established the fundamental architecture for web-based GPS-GPRS vehicle tracking platforms, demonstrating the viability of accessible systems for real-time monitoring. Additionally, Peppes et al. (Peppes et al., 2021) presented a comprehensive platform that combines real-time data streaming with machine learning algorithms for analyzing driving behavior. Their hybrid architecture uses Apache Kafka for streaming, MySQL and MongoDB for storage, and Hadoop with PySpark for big data analysis. The platform processed over 20 million data points from 5 operational vehicles, demonstrating scalability and viability for massive implementations in production environments. Moreover, Duran and Earleywine (Duran & Earleywine, 2012) established fundamental methodologies for filtering and processing raw GPS data, addressing typical errors such as signal loss, outliers, zero-speed drift, and white noise. Their seven-step sequential filtering process significantly improves data quality for vehicular applications, reducing alterations to less than 1% in light vehicle data and 0.5% in heavy vehicles, excluding signal discontinuities.

Although these platforms demonstrate advanced technical capabilities for GPS data capture and processing, Castignani et al. (Castignani et al., 2015) emphasize the importance of balancing technological capacity with economic viability, proposing a low-cost platform for continuous driver monitoring that demonstrates technical and financial feasibility for widespread implementation. This balance between technical sophistication and accessibility is crucial for the practical adoption of behavioral intervention systems.

2.2 Aggressive Driving Detection

Research in vehicular monitoring has undergone significant evolution with the development of mobile technologies. Zhao et al. (Zhao et al., 2018) analyzed driving behavior using real GPS data from 108 participants over a two-month period, demonstrating the value of continuous GPS data for large-scale behavioral analysis. Their methodology for processing large volumes of tracking data and integration with digital mapping systems established essential precedents for vehicular monitoring platforms. The findings contradicted self-reported perceptions, validating the importance of objective versus subjective monitoring.

Mantouka et al. (Mantouka et al., 2021) demonstrated that smartphones can achieve accuracies of 96-99% in detecting aggressive driving behaviors using integrated inertial sensors. This high precision is comparable to professional OBD-II systems, as confirmed by Wahlström et al. (Wahlström et al., 2017) in their ten-year review of smartphone-based vehicle telematics. Moreover, Johnson and Trivedi (Johnson & Trivedi, 2011) developed driving-style recognition algorithms using smartphones as sensor platforms, successfully classifying aggressive, normal, and cautious driving patterns. Their work established the foundations for automatic differentiation of driving behaviors using accelerometers and gyroscopes integrated into mobile devices.

Likewise, the D&RSense work presents a system for real-time detection of aggressive driving using GPS and accelerometer in smartphones, employing Random Forest algorithms to classify events and map areas prone to risky driving (Z. Chen et al., 2015). Finally, White et al. (White et al., 2011) developed a framework for categorizing aggressive maneuvers using only smartphone data, achieving accuracies above 90% in controlled conditions. However, these works focus exclusively on algorithmic detection precision without evaluating the actual impact on driver behavior in natural driving environments. Precise detection is necessary but insufficient, as it does not translate into effective behavioral changes.

2.3 Driving Interventions

Mohd Zaki et al. (Mohd Zaki et al., 2021) conducted a systematic review on auditory alerts for vehicle safety technologies, establishing that 70% of drivers deactivate alarms due to annoying audio characteristics. Their analysis of automotive manufacturers revealed necessary frequency configurations between 300 and 3200Hz, with ISO 15006:2011 recommendations of 500-2500Hz and sound pressure levels of 50-90dB(A). These standards are crucial for designing effective and user-acceptable auditory feedback systems, as a technically precise but perceptually annoying system will fail due to user rejection.

The most relevant study in terms of scale and methodological rigor was conducted by the AAA Foundation for Traffic Safety (Ebert et al., 2025), which evaluated 1,400 participants divided into control and various feedback groups using mobile applications over 24 weeks. Their results show significant reductions of 13% in speeding, 21% in harsh braking, and 25% in sudden accelerations. More importantly, these positive changes were sustained even after the feedback period ended, suggesting long-term effects. However, this study used weekly text message feedback rather than immediate auditory feedback during driving, which represents a fundamental difference in the timing of the intervention.

Additional studies have explored various intervention modalities, albeit with considerably smaller samples. For instance, an alert system combined with economic incentives was evaluated in 50 participants, finding modest changes that were more pronounced when financial incentives were included (Gao et al., 2010). Additionally, smartphone-based ADAS systems evaluated by Thompson et al. (Thompson et al., 2019) in 24 participants demonstrated improvements in safe driving with good user acceptance. The BackPocketDriver system (Arvin et al., 2019) evaluated pre- and post-intervention changes in 20 drivers using feedback via a mobile application.

In another instance, Tarqui et al. (Tarqui et al., 2011) investigated the use of mobile technology to reduce driver distractions through landmark-based navigation assistants, finding improvements in attention and reduction of risky behaviors. Additionally, research by Mantouka et al. (Mantouka et al., 2019) employed machine learning techniques to identify driving safety profiles from smartphone data, establishing that aggressive behavior patterns can be detected and classified with high precision.

Most studies focus on periodic reports with latencies of days or weeks (Ebert et al., 2025), (Gao et al., 2010), (Arvin et al., 2019), rather than on immediate interventions during the aggressive driving event. This temporal difference is fundamental to operant conditioning. While delayed feedback requires the driver to remember and mentally associate past behaviors with the feedback received, immediate feedback provides a direct and automatic association between behavior and consequence.

Additionally, sample sizes vary considerably in the literature, ranging from small case studies with 20-50 participants (Thompson et al., 2019), (Arvin et al., 2019) to large-scale investigations, such as the AAA Foundation with 1,400 participants (Ebert et al., 2025). However, no study evaluates explicitly immediate auditory feedback with appropriate control groups. The AAA Foundation study, although robust in terms of sample size and duration (24 weeks), used weekly text-message feedback, which introduces a delay of up to 7 days between observed behavior and feedback.

2.4 Cognitive Processing in Driving

Understanding how drivers process different maneuvers is fundamental for designing effective interventions. Kahneman's dual-process theory (Kahneman, 2011) establishes that the human brain operates through two systems: System 1 (automatic, fast, intuitive) and System 2 (deliberate, slow, analytical). In the driving context, this distinction is crucial for understanding why different behaviors respond differentially to feedback interventions.

For experienced drivers under routine conditions, many actions are executed through System 1. McKenna (McKenna, 2016) argues that highly practiced tasks, such as maintaining constant speed or accelerating smoothly on familiar routes, require minimal cognitive resources, operating in "autopilot" mode. This automaticity allows the driver to perform multiple tasks simultaneously without significant degradation of performance in routine driving.

In contrast, braking frequently requires transition to System 2, especially in responses to unexpected stimuli. Engström et al. (Engström et al., 2017) demonstrated that cognitive load negatively affects braking reaction times, evidencing that braking depends on deliberate cognitive control. This finding is consistent with classic studies such as that by Brown et al. (Brown et al., 1969), who found that while speed control remains stable under secondary cognitive load, performance in braking tasks deteriorates significantly, suggesting that braking is not a completely automated process.

This cognitive differentiation has direct implications for immediate feedback systems. Deliberate behaviors (System 2) such as braking, which require conscious evaluation of distance, speed, and necessary force, should be more susceptible to modification through immediate external signals. Conversely, more automated behaviors (System 1), such as routine acceleration, may exhibit greater resistance to feedback interventions, possibly requiring different or more prolonged intervention strategies to achieve significant behavioral changes.

2.5 Persuasive Technology and Behavior Change

The design of effective systems for modifying driving behaviors is based on principles of persuasive technology and Behavior Change Support Systems (BCSS). Fogg (Fogg, 2003) established the foundations of captology, the study of how computers can be designed to influence attitudes and behaviors without coercion. His Behavior Model (Fogg Behavior Model) posits that for a target behavior to occur, three elements must converge simultaneously: motivation (the desire to act), ability (the ease of executing it), and a prompt (a signal that triggers the action). This formula, B = MAP (Behavior = Motivation + Ability + Prompt) (Fogg, 2009), is fundamental for understanding why immediate auditory feedback can be effective. It acts as an instantaneous prompt at moments of high motivation (personal safety) when the driver has full ability to modify their behavior (during active driving).

Oinas-Kukkonen and Harjumaa (Oinas-Kukkonen & Harjumaa, 2009) developed the Persuasive Systems Design (PSD) Model, which organizes design principles into four categories: primary task support, dialogue support, system credibility, and social support. Immediate auditory feedback aligns specifically with two of these categories. First, primary task support is achieved by reducing the effort required for self-monitoring: instead of the driver having to remember to review their behavior consciously, the system does it automatically. Second, dialogue support is provided through immediate feedback that keeps the driver informed about their performance in real-time, implementing the "feedback" principle that is central to behavior change interventions.

The Behavior Change Technique Taxonomy (BCTTv1) by Michie et al. (Michie et al., 2013) identifies 93 distinct techniques for modifying behaviors. Our system implements explicitly three BCTs: (1) behavior self-monitoring through automatic detection of aggressive events, eliminating the need for manual recording; (2) feedback on behavior through immediate auditory alerts that inform the driver when they engage in risky maneuvers; and (3) cues/reminders that act as environmental prompts at the exact moment of the unwanted behavior. These techniques are consistent with effective interventions in the behavior change literature, where immediate feedback is more effective than delayed feedback for behaviors requiring real-time correction (Ebert et al., 2025), (Fogg, 2009).

The critical distinction between our approach and delayed feedback systems lies in the temporality of the prompt. While applications such as those evaluated by the AAA Foundation (Ebert et al., 2025) provide weekly feedback that requires the user to remember and mentally associate past behaviors, our system implements immediate prompts that, according to Fogg's model (Fogg, 2009), have a higher probability of resulting in behavior change by eliminating the cognitive load of remembering and associating. The immediacy principle in BCSS establishes that the lower the latency between behavior and feedback, the more effective the intervention will be in modifying that specific behavior.

3 Methods

In this section, we present the methods used in this work.

3.1 Materials and Instruments

The hardware employed included professional GPS devices, such as the JIMIIOT VL104 with OBD-II connection for precise vehicle monitoring, inspired by Castignani et al.'s (Castignani et al., 2015) methodology for low-cost systems. The smartphones used contained a customized application for auditory alerts, based on principles established by Johnson and Trivedi (Johnson & Trivedi, 2011) for detecting driving patterns. The EPCOMGPS management platform enabled storage, GPS data analysis, and notifications, following the recommendations of Wahlström et al. (Wahlström et al., 2017) for mobile telematics systems.

The software included detection algorithms with calibrated thresholds for aggressive events greater than 0.25g for acceleration and greater than 0.30g for braking and turns, based on standards established by Mantouka et al. (Mantouka et al., 2021). The alert system provided immediate auditory notifications via smartphone with 500ms beeps for the experimental group, implementing immediate feedback principles described by the AAA Foundation (Ebert et al., 2025). The auditory alert design prioritized user acceptance alongside effectiveness. Research by Mohd Zaki et al. (Mohd Zaki et al., 2021) found that 70% of drivers deactivate safety alerts due to annoying characteristics. Our implementation employed a brief (500ms), neutral beep, intentionally designed to be informative rather than alarming, aiming for cognitive awareness without emotional burden or startle response that could compromise safety or lead to system rejection. The analysis platform automatically processed GPS data and generated per-kilometer metrics.

A 11-item post-experiment questionnaire was developed to assess subjective perceptions and system acceptance, with items adapted from established technology acceptance scales (Joshi et al., 2015) and driving behavior assessment instruments.

3.2 Variables

The independent variable was the type of feedback received: no feedback versus auditory feedback. The dependent variables are as follows. All dependent variables were normalized per kilometer traveled to control for differences in travel distances. We computed the following values for this study.

- Harsh acceleration. Number of acceleration events greater than 0.25g per kilometer
- Harsh braking. Number of deceleration events greater than 0.30g per kilometer.
- Aggressive turns. Number of lateral force events greater than 0.30g per kilometer.
- Speeding. Number of alerts for exceeding established speed limits by more than 15 km/h per kilometer.

The detection thresholds employed (0.25g for acceleration and 0.30g for braking and turns) are based on standards established by vehicle telematics research, where 1g equals Earth's gravitational acceleration (9.81 m/s^2). These values have been validated by Mantouka et al. (Mantouka et al., 2021) as effective indicators for distinguishing between normal and aggressive driving behavior. They are widely used in the vehicle monitoring industry and usage-based insurance programs. Selecting these thresholds allows capturing driving events that exceed the range of typical accelerations during everyday driving, providing an objective basis for classifying aggressive behaviors.

The following subjective variables were measured through a questionnaire administered at the end of the day:

3.3 Perception and awareness measures

- Driving perception of the day: Ordinal 5-point scale evaluating whether the participant considered their driving more aggressive or more careful than their usual driving (1=Much more aggressive, 2=Somewhat more aggressive, 3=Same as always, 4=Somewhat more careful, 5=Much more careful).
- Monitoring awareness: Categorical variable with four levels evaluating whether the participant noticed the recording equipment and how this affected their driving (1=Did not notice at all, 2=Noticed but it did not affect me, 3=Noticed and it made me drive more carefully, 4=Noticed and it made me nervous/uncomfortable).
- Self-perception of harsh maneuvers: Categorical variable with four levels about the estimated quantity of aggressive events during the day (1=None or very few, 2=Some few (< 10), 3=Several (10-30), 4=Many (> 30)).
- Most frequent maneuver type: Categorical variable identifying which type of aggressive behavior the participant considered most frequent in their driving that day (1=Accelerating very hard, 2=Braking abruptly, 3=Turning very sharply, 4=Driving dangerously, 5=Exceeding speed limits, 6=I don't think I made harsh maneuvers).

3.3.1 System acceptance measures

We also collected the following data regarding the participants' perception of several aspects of the system:

***Table 1**: Participants' demographics*

ID	Group	Age	Gender	Occupation	Marital Status
P2	Experimental	22	Male	Student	Single
P3	Experimental	23	Male	Employee	Single
P4	Experimental	24	Female	Employee	Single
P5	Experimental	53	Female	Secretary	Married
P1	Control	27	Male	Engineer	Single
P6	Control	24	Female	Accountant	Single
P7	Control	27	Male	Programmer	Single
P8	Control	25	Male	Employee	Single

- Perceived system utility: Single-item 7-point Likert scale evaluating how useful the participant considers having a system that detects harsh or dangerous driving (1=Not useful at all, 7=Very useful). This item was adapted from standard technology acceptance questionnaires (Joshi et al., 2015).
- Awareness of driving style: Single-item 7-point Likert scale evaluating whether participating in the study helped the participant realize how they actually drive (1=Not at all, 7=Very much). This measure assesses metacognitive awareness gained through exposure to the system.
- Perceived behavioral change: Categorical variable with four levels about self-reported changes in driving behavior due to having equipment installed (1=Did not change at all, 2=Changed a little at the beginning, then drove normally, 3=Changed moderately throughout the day, 4=Changed a lot, drove more carefully all day).
- Adoption intention: Ordinal categorical variable with five levels about willingness to install the system in their personal vehicle (1=Definitely not, 2=Probably not, 3=Maybe, 4=Probably yes, 5=Definitely yes).
- Willingness to recommend: Categorical variable with five levels about recommending the system to other drivers (1=Definitely would not recommend it, 2=Probably would not recommend it, 3=Would only recommend it to specific drivers, 4=Yes, to young drivers or those who drive aggressively, 5=Yes, to all drivers).

Both experimental and control groups completed identical questionnaires focused on "vehicle monitoring systems" generally, not specifically on auditory alerts. During informed consent, all participants were informed that they would participate in a study on "how to detect and improve driving habits using GPS technology." Both groups had visible GPS devices installed and were aware that they were being monitored. This design enabled the control group to evaluate passive monitoring (GPS tracking without intervention), while the experimental group evaluated active feedback systems (monitoring plus immediate alerts). This approach addresses the critical question: Do immediate auditory alerts improve acceptance and awareness compared to passive monitoring alone?

These nine measures were operationalized through an 11-item questionnaire administered immediately after the monitoring period (see Procedure, Section 3.6). The questionnaire included both closed-ended items with Likert and categorical scales, and three open-ended questions for qualitative feedback.

3.3.2 Control Variables

Control variables included total distance in kilometers during the session, driving time (total session duration), road type (proportion of urban versus suburban roads), and average and maximum speed as indicators of general driving style.

3.4 Participants

The study included 8 non-professional drivers (5 male, 3 female) recruited in a mid-size city in northwestern Mexico with approximately 100,000 inhabitants. Ages ranged from 22 to 53 years (M=28.1, SD=9.8).

Table 1 presents detailed demographic profiles. Participants represented a diverse range of occupational backgrounds, including students, office employees, and professionals. All participants held valid driver's licenses with a minimum of 2 years of driving experience and drove regularly for personal or professional purposes. Inclusion criteria were: (1) a valid driver's license, (2) a minimum of 2 years of driving experience, (3) a non-professional private driver status, and (4) availability to drive at least 10 km during the experimental day.

Participants were randomly assigned to groups based on availability and scheduling, with group assignment (experimental vs. control) determined before recruitment. The experimental group (n=4) included participants P2, P3, P4, and P5. The control group (n=4) included participants P1, P6, P7, and P8. Groups were comparable in age: the experimental group (M=30.5, SD=15.02) and the control group (M=25.8, SD=1.5). However, the experimental group showed greater age variability due to the inclusion of one older participant (P5, age 53).

All participants drove their normal daily routines during the monitoring period, which included commuting between home and work as well as additional errands throughout the day. The distance traveled varied considerably among participants (range: 13-100 km, M=38.6, SD=30.5), with the longest route approximately 7 times greater than the shortest. This variability reflects natural differences in individual daily driving patterns rather than experimental manipulation. All dependent variables were normalized per kilometer traveled to ensure equitable comparisons across participants with different total distances.

3.5 Data Analysis

Data were analyzed with Student's t-tests for independent samples. Python was used for data analysis.

3.6 Procedure

The study employed a single-day between-subjects experimental design developed in three main phases.

- Preparation phase: Conducted between 7:00-8:00 AM and included installation of the GPS device VL104 in the vehicle's OBD-II port and smartphone configuration with experimental application. The smartphone was configured at this stage rather than in advance to prevent participants from familiarizing themselves with the application interface prior to the study. The smartphone served solely as a medium to deliver auditory alerts to the experimental group and did not require participant interaction. Both systems' functioning was verified before departure. Participants received standardized verbal instructions based on the informed consent document: "You will participate in a study on how to detect and improve driving habits using GPS technology. This device will detect events such as harsh acceleration, harsh braking, sharp turns, dangerous driving, or speeding. Please drive normally through your daily activities until 5:00 PM. At the end of the day, we will remove the equipment and ask you some questions. Your responses are completely confidential and will be used solely for academic research purposes." All participants signed informed consent before installation.
- Monitoring phase: Extended from 8:00 AM to 6:00 PM. During this phase, the Control Group operated with an active GPS for data recording and a silent smartphone without alerts. The Experimental Group operated with an active GPS plus immediate auditory feedback triggered by detected aggressive driving events (as defined in Section 3.2) through the smartphone application.
- Closure and questionnaire phase: Conducted between 6:00 and 8:00 PM. This phase included the removal of equipment, immediate GPS data download, verification of data quality and integrity, administration of a post-experiment questionnaire lasting 5-10 minutes, and automatic backup to cloud platforms.
- Technical Implementation Details: The VL04 GPS device transmitted data via GPRS to the EPCOMGPS cloud platform, which triggered push notifications to the smartphone application when aggressive driving events exceeded calibrated thresholds. The system was configured with high data transmission rates to ensure immediate feedback with minimal latency. GPS data were downloaded from the EPCOMGPS cloud platform via web interface at the end of each monitoring session. Data quality verification included: (1) identifying and removing false positives, (2) detecting duplicate events recorded at identical timestamps to prevent double-counting, and (3) confirming that simultaneous alerts represented distinct events rather than repeated detections of the same maneuver. All data were automatically backed up within the EPCOMGPS platform.
- Ethical Considerations: The protocol was designed following ethical principles for human participant research.

All participants provided written informed consent prior to the study, detailing the data collected (i.e., GPS location, acceleration events, speed), the duration of monitoring (8-10 hours), and their right to withdraw at any time without penalty. Location data were immediately anonymized using numerical participant IDs with access restricted to the research team. Specific addresses were never extracted or analyzed, and no data were shared with third parties.

The protocol minimized risks through several measures: a) auditory alerts were designed to be informative without causing startle or excessive distraction, b) we provided participants a contact number for technical support during the day, and c) they could discontinue participation at any time. The brief (500ms), non-alarming tone was chosen to avoid triggering dangerous reactions such as sudden braking or swerving. All procedures prioritized driver safety and data confidentiality throughout the study.

4 Results

The group with feedback showed 37% fewer total aggressive events per km (0.899 vs 1.433) and 70% fewer harsh braking events per km (0.124 vs 0.421) (Table 2). Variability was considerably greater in the group without feedback, suggesting differential effects across individuals.

Although no comparison reached conventional statistical significance ($p < 0.05$), harsh braking showed a marginally significant trend ($p = 0.072$) with a very large effect size ($d = -1.424$). Total aggressive events also showed a large effect size ($d = -0.745$, $p = 0.274$) (Table 2).

Participants who received feedback reported greater awareness of their driving (M=6.25, SD=1.26) compared to the control group (M=4.75, SD=0.96), representing a 32% increase in metacognitive awareness. The system utility was rated highly across both groups, with the feedback group at M=6.75 (SD=0.96) and the control group at M=6.25 (SD=0.96) (Table 3), indicating a substantial perceived value of monitoring technology in general. Regarding behavioral change perception, 50% of the experimental group (2/4 participants) reported moderate to significant changes in their driving throughout the day, compared to 25% (1/4) of the control group. Adoption intention was equivalent across groups (50% in both), while willingness to recommend was higher in the feedback group (50% vs 25%) (Table 3).

Objective data and subjective perceptions showed some concordance, where participants who reported greater awareness of their driving effectively demonstrated reductions in aggressive events, particularly in instances of harsh braking. This concordance suggests that auditory feedback not only modifies behavior but also increases self-perception of risk. The high acceptance scores (M≥6.25/7) combined with objective behavior reductions (70% fewer harsh braking events, 37% fewer total aggressive events) demonstrate that immediate auditory feedback can be both practical and acceptable when designed following appropriate psychoacoustic principles, avoiding the alert annoyance and system rejection (Mohd Zaki et al., 2021).

5 Discussion

This pilot study provides preliminary evidence that immediate auditory feedback can reduce aggressive driving behaviors, particularly harsh braking events. The 70% reduction in aggressive braking (Cohen's d = -1.424) represents a substantial effect that, although it did not reach conventional statistical significance given the limited sample size (N=8), suggests important practical potential. The between-subjects experimental design with a control group enables estimation of effect magnitudes essential for designing adequately powered confirmatory studies. The results are consistent with the AAA Foundation study (Ebert et al., 2025), which found a 21% reduction in harsh braking with delayed feedback. Our finding of a 70% reduction with immediate feedback suggests that temporal proximity between behavior and consequence can significantly amplify the effectiveness of interventions.

Fundamental differences in the cognitive processing of these maneuvers can explain the greater effect of harsh braking compared to acceleration. Based on Kahneman's dual-process theory (Kahneman, 2011), braking typically represents a deliberate behavior that requires System 2 (analytical and conscious processing), while acceleration under routine conditions operates through System 1 (automatic processing) (McKenna, 2016). This distinction is supported by empirical evidence: Engström et al. (Engström et al., 2017) demonstrated that performance in braking tasks deteriorates significantly under cognitive load, whereas automated tasks such as speed control remain stable (Brown et al., 1969). Preliminary data from our study suggest that auditory feedback may be more effective for modifying behaviors that require conscious processing, as indicated by the observed effect size (Cohen's d = -1.424 for harsh braking vs. d = -0.174 for acceleration). This difference in effectiveness is consistent with the theoretical prediction that deliberate System 2 behaviors, which demand active evaluation and decision-making, are more susceptible to modification through immediate external signals than automated System 1 behaviors. However, confirmation with larger samples and studies that specifically evaluate underlying cognitive mechanisms is required.

The concordance between subjective perceptions and objective changes suggests that auditory feedback increases metacognition about driving behavior, facilitating self-control. Participants not only reduced aggressive behaviors but also developed greater awareness of their driving patterns.

The effectiveness of immediate feedback aligns with principles of interaction design, emphasizing that feedback should be immediate and informative to support learning (Nielsen, 1994), (Norman, 1988). Our system provides auditory alerts with minimal latency after detecting aggressive behavior, thereby creating a tight temporal coupling between the behavior and its consequences. This contrasts with delayed systems, which provide weekly or monthly reports (Ebert et al., 2025), (Oinas-Kukkonen & Harjumaa, 2009) that require retrospective recall and increase cognitive load. The principle of "visibility of system status", continuously informing drivers when thresholds are exceeded, enables real-time adjustment rather than post-hoc reflection. The convergence of high acceptance (M≥6.25/7), objective reductions (70% fewer harsh braking events), and increased awareness (32% improvement) demonstrates that immediate feedback satisfies both effectiveness and usability requirements critical for the deployment of persuasive safety technology (Fogg, 2003), (Fogg, 2009), (Oinas-Kukkonen & Harjumaa, 2009).

5.1 Limitations

The main limitation was the sample size (N=8), which resulted in insufficient statistical power to detect significant differences. Although total aggressive events showed a large effect size (d = -0.745), they did not reach statistical significance (p = 0.274, t = -1.244, df = 4.45). The large effects observed in harsh braking (d = -1.424, p = 0.072) suggest that with greater N, statistical significance would be achieved. For medium effects (d = 0.5) with adequate power (0.8), approximately 30 participants per group are required. The single-day design does not allow for evaluating long-term effects or habituation to feedback. Longitudinal studies are necessary to determine whether benefits are maintained with prolonged exposure. The high variability in the control group suggests critical individual differences in driving patterns. The results are derived from a specific context in northwestern Mexico with private drivers. Generalization to other populations, cultural contexts, or types of professional or elderly drivers requires additional research.

5.2 Future Research Directions

Several promising directions emerge from this pilot study. Future research should investigate different types of auditory signals (e.g., tones, words, music) and their differential effects, evaluate feedback personalization according to individual preferences or demonstrated effectiveness, and examine variables such as age, gender, driving experience, and personality influence response to auditory feedback to develop adaptive algorithms. Longitudinal studies should evaluate the persistence of long-term effects and habituation phenomena, while multimodal approaches could combine auditory feedback with visual and haptic modalities to maximize effectiveness without saturating the driver.

Additionally, future work should analyze contextual factors such as road type characteristics (urban vs. suburban density, pavement quality), geographic clustering of aggressive events, and vehicle maintenance conditions. Integrating GPS coordinate mapping with road classification APIs and maintenance logs would enable the identification of situational moderators, supporting the development of context-aware adaptive feedback systems optimized for specific driving environments and vehicle conditions.

6 Conclusions

This pilot study provides preliminary but promising evidence that immediate auditory feedback can reduce aggressive driving behaviors, especially harsh braking events. Large effect sizes (Cohen's d = -1.424 for harsh braking, d = -0.745 for total aggressive events) suggest substantial practical significance, although studies with greater statistical power are required to confirm these findings. The rigorous between-subjects experimental design establishes methodological foundations and effect size estimates that enable future confirmatory research with appropriately powered samples (N ≥ 30 per group).

The hybrid GPS-smartphone technology demonstrated technical viability and high user acceptance (scores > 6.2 on a 1-7 scale), creating opportunities for large-scale deployment of behavioral modification systems. The concordance between objective changes and subjective perceptions suggests that feedback not only modifies behavior but also increases metacognition about driving patterns.

The main contributions of this work include empirical evidence of the effectiveness of immediate auditory feedback, surpassing previous studies with reductions of 70% vs. 21% in harsh braking, validation of hybrid GPS-smartphone systems for behavioral interventions, and identification of differentiated psychological mechanisms according to the type of behavior, conscious versus automated.

We recommend conducting replication with larger samples (N ≥ 30 per group) to confirm the statistical significance of the large effects observed. Longitudinal studies to evaluate persistence of effects and habituation, and investigation of moderating factors to optimize feedback personalization. The demonstrated potential of these technologies to enhance road safety justifies investment in further research.

7 Declarations

Author Contributions (CRediT)

Conceptualization: W.F.P., L.A.C.; **Data curation:** W.F.P.; **Formal analysis:** W.F.P., L.A.C.; **Funding acquisition:** L.A.C.; **Investigation:** W.F.P., L.A.C.; **Methodology:** W.F.P., L.A.C.; **Project administration:** W.F.P., L.A.C.; **Resources:** W.F.P., L.A.C.; **Software:** W.F.P., L.A.C.; **Validation:** W.F.P., C.B.P.; **Visualization:** W.F.P.; **Writing – original draft:** W.F.P., L.A.C., C.B.P, J.V.N.; **Writing – review and editing:** W.F.P., L.A.C., C.B.P, J.V.N.

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Conflicts of Interest

The author declares no conflicts of interest.

Data, Code, and Materials Availability

The data are not publicly available due to privacy restrictions of the participants, as they include geolocation information that could compromise their identity. Anonymized and aggregated data are available from the corresponding author upon reasonable request.

Ethical Approval and Informed Consent

All participants provided signed informed consent prior to their participation, authorizing the use of their driving data and their voluntary participation in the experimental procedure. The consent form covered data usage and participation in the experiment. This study was conducted as an academic project at the Instituto Tecnológico de Sonora; no formal institutional ethics committee approval was obtained, given the educational and low-risk nature of the research.

Consent for Publication

Not applicable, as no identifiable information about the participants is included in this manuscript. All data were anonymized.

Declaration of Generative AI Use

Generative AI (Claude, Anthropic) was used solely to assist with translation and grammatical review of the manuscript. The tool did not participate in the experimental design, data collection, statistical analysis, or interpretation of results. All scientific content, analysis, and conclusions reflect the author's own work and judgment.

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