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Professional Pilot Transumo IV - Study on a Safest-route Functionality with Financial Incentive for Professional Drivers

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Samenvatting

De centrale doelstelling van het Transumo project Intelligent Vehicles was om in-car telematica als een baanbrekende technologie te gebruiken om de kwaliteit van reizen en duurzaam wegverkeer te verbeteren en de waarde van de mogelijkheden van in-car telematica te waarderen in termen van veiligheid, doorstroming, betrouwbaarheid en milieu.

Binnen het kader van het Transumo project Intelligent Vehicles is het subproject met de titel ‘professional pilot’ uitgevoerd. Het doel van deze pilot was om door middel van een financiële beloning beroepschauffeurs te stimuleren een veiligere route te laten volgen. In de pilot is onderzocht hoe het doel gerealiseerd kan worden.

In een literatuuroverzicht werd geconcludeerd dat de relatie tussen de routekeuze en de veiligheid niet vaak beschreven is in de wetenschappelijke literatuur. Een studie werd gevonden waar niet-professionele bestuurders in plaats van beroepschauffeurs in deelnamen. Het concept van het beïnvloeden van de routekeuze van beroepschauffeurs lijkt daarom een onontgonnen terrein te zijn.

Voor de theoretische en praktische uitvoering van de pilot zijn verschillende componenten onderzocht. Ten eerste werd een algemeen model voor de beloningsstructuur geponeerd. Dit conceptuele model werd gebruikt als basis voor twee studies die uitgevoerd werden in het kader van de professional pilot. Ten tweede is het veiligste route algoritme beschreven. In de literatuur vindt men algoritmen voor het bepalen van een snelste route of kortste route. Echter, kant en klare algoritmen voor een veiligste route waren niet beschikbaar. Daarom werd een veiligste route algoritme ontwikkeld, gebaseerd op de 'Duurzaam-Veilig' criteria.

Daarnaast zijn drie studies verricht in het subproject ‘professional pilot’. In de eerste studie is onderzocht of een chauffeur in toekomstige situaties bereid zou zijn om een veiligere route te kiezen als er een beloning werd gegeven. In de tweede studie is onderzocht of chauffeurs daadwerkelijk een veiligere route zouden kiezen als er een beloning werd gegeven. Tot slot werd een derde studie uitgevoerd om te bepalen wat de kans is dat overheden, de automobielindustrie en verzekeringsmaatschappijen bepaalde implementatieopties (bijvoorbeeld het uitkeren van beloningen wanneer er veilig wordt gereden) in toekomstige situaties zouden gaan toepassen.

Zoals gezegd, de eerste studie werd uitgevoerd om de bestuurdersreactie op beloningen te beoordelen en daarmee de mogelijke voordelen van veilige routes te kunnen bepalen. Voor deze studie werd een route gebaseerd beloningsprogramma geïntroduceerd.
In totaal hebben 45 Nederlandse chauffeurs deelgenomen aan een enquête over hun verwachte gedrag bij een beloningsprogramma zoals uitgevoerd in de praktijktest, in voorbereiding op deelname aan de praktijktest. De resultaten toonden aan dat de bestuurders de neiging hadden om de veiligheidsgerelateerde informatie te negeren bij het maken van hun routekeuze. Daarentegen had de beloning een significant effect op de routekeuze. Belonen lijkt daarom een efficiënte manier om de routekeuze te beïnvloeden. De online enquête die in deze studie werd toegepast is een ‘stated preference’ techniek, een techniek om het gedrag van de bestuurder in toekomstige situaties te onderzoeken.

De tweede studie omvatte het grootste deel van het Transumo-project en had als onderzoeksvraag hoe groot de daadwerkelijke invloed van een beloning op de routekeuze is (revealed preference). Tijdens deze Field Operational Test, die 2 maanden duurde, werden het rijgedrag en de routekeuze van beroepschauffeurs gemeten.
De voertuigen waren uitgerust met een navigatiesysteem die een snelste en veiligste route naar een opgegeven bestemming kon berekenen. Telematica technologie werd succesvol ingezet om de routes te berekenen. Na een maand werden de deelnemers beloond wanneer ze de veiligste route reden. De gebruikte route-algoritmen zijn vergeleken in een steekproef van herkomst- en bestemmingspunten. In de vergelijking tussen de daaruit voortvloeiende veiligste en snelste route, werd vastgesteld dat bij 78% van de gevallen de routes gelijk waren. Dit resultaat is een belangrijke voorwaarde voor het duurzaam veilig principe waar men is gericht op zowel veilige als snelle routes.
Voor de resterende 22% van de gevallen waren er verschillen tussen de snelste en veiligste routes. De afgelegde afstand voor de veiligste route was langer in vergelijking met de snelste route. De verschillen werden veroorzaakt door een toename van de afgelegde afstand op snelwegen en erftoegangswegen. Het veldexperiment laat echter geen positief effect op het gebruik van die beloning zien, zoals verondersteld was.
Er zijn vele mogelijke oorzaken die van invloed kunnen zijn op het gevonden resultaat. Het belangrijkste punt is dat beide systemen verschilden met betrekking tot de functionaliteit en bruikbaarheid, het berekenen van de snelste route ging bijvoorbeeld veel sneller dan het berekenen van de veiligste route. Bovendien, als gevolg van diverse technologische tegenslagen, is de meetperiode van de pilot ingekort. Vanwege de beperkte meetperiode is het daarom mogelijk dat er een effect van de beloning op de route keuze was maar dat het effect niet gevonden werd.

De derde studie werd uitgevoerd om te bepalen wat de kans is dat overheden, de automobielindustrie en verzekeringsmaatschappijen bepaalde implementatie opties gaan toepassen om de gebruiker te beïnvloeden om bestuurdersondersteunende systemen aan te schaffen, en de kans dat gebruikers deze systemen ook daadwerkelijk aanschaffen gegeven deze implementatie opties. Hiertoe is een enquête gehouden onder stakeholders en gebruikers, waarin gebruik is gemaakt van de stated preference methodologie, om modellen te kunnen schatten van stakeholder- en gebruikersbeslissingen. Op het stakeholderonderzoek zijn 75 reacties ontvangen waarvan 72 bruikbaar, op het gebruikersonderzoek zijn 250 reacties ontvangen. Drie verschillende bestuurdersondersteunde systemen werden beschouwd (voor ieder systeem werd verwacht dat een specifieke stakeholder het initiatief zou nemen) en drie implementatie opties waren opgenomen voor elke stakeholder (niets doen, stimuleren of verplichten).
De verschillende bestuurdersondersteunende systemen bleken geen invloed te hebben op de kans dat stakeholders een bepaalde implementatie optie toepassen.
De implementatie opties van de stakeholders zelf, en in mindere mate die van andere stakeholders, hadden de meeste invloed op deze kans. Verder werd geconstateerd dat de kans dat gebruikers ervoor kiezen om een bestuurdersondersteunend systeem aan te schaffen in hoge mate afhankelijk is van financiële prikkels.

Samenvattend: Een veiligste route algoritme is ontwikkeld en geïmplementeerd.
Dit algoritme is succesvol gevalideerd. In een enquête gaven chauffeurs aan bereid te zijn om een veiligere route te kiezen als er een beloning werd gegeven. Helaas is in de veldproef nog niet voldoende bewijs gevonden dat chauffeurs ook daadwerkelijk een veiligere route volgen. Daarnaast is het nog onzeker of de overheid of verzekeringsmaatschappijen werkelijk bereid zullen zijn om deze beloningen te gaan verstrekken.

Summary

The main objective of the Transumo project Intelligent Vehicles was to use in-vehicle telematics as a breakthrough technology to improve the quality of travel and sustainable road traffic and to appreciate the potential of in-car telematics in terms of safety, throughput, reliability and environment.

The subproject "Professional Pilot" is performed within the framework of the Intelligent Vehicles Transumo project. The aim of this pilot was to influence the route choice behaviour of professional drivers by providing a financial incentive for following a safest route. The pilot addressed how this goal can be achieved.

In the literature review it was concluded that the relationship between route choice and safety is not often described. One study was found, were the focus was on private drivers instead of professional drivers. Therefore, the concept of influencing the route choice to a safest route for professional drivers appeared to be new.

For the theoretical and practical implementation, two different components have been explored. Firstly, a general model for the incentive program was proposed. This conceptual model was used as a basis for two studies conducted within this research. Secondly, a safest route algorithm was developed and described. In the literature, one can find algorithms to determine a fastest route or shortest route. However, ready-to-use algorithms for a safest route were not available. Therefore, a safest route algorithm was developed based on existing ‘Duurzaam-Veilig (Sustainable Safety)’ criteria.

Besides the exploration, three studies have been undertaken in this part of the Transumo project Intelligent Vehicles. The first study was undertaken to assess the drivers’ response to incentives and thereby the potential benefit of safest routes advice with incentive. This study introduced a route-based incentive program operated by a logistic company together with an insurance company. In total 45 Dutch professional drivers participated in a survey about expected behaviour in case of a rewarding scheme for safest routes as implemented in the professional pilot, as preparation of participation in the professional pilot. The results showed that drivers tend to ignore safety-related information in making their route choices; however, the incentives had a significant effect on these choices. The incentives therefore seem to present an efficient way of influencing drivers’ route choices. The online survey used in this study is a stated preference technique to investigate driver behaviour in future situations. When the incentive program is put into practice, the actual driver behaviour (i.e. revealed preference) may differ.

The second study, the main part of this Transumo subproject, was conducted to determine the revealed preference, i.e., whether incentives have a significant effect on the route choice in practice. During the Field Operational Test, which lasted for 2 months, the driving behaviour and route-choice of professional drivers were unobtrusively measured. The vehicles were equipped with a navigation system, which could generate a fastest and a safest route to a given destination. After one month, the participants were also rewarded when they drove the safest route. The used route algorithms have been compared for a sample of origin-destination points taken from the field operational test. In the comparison between the resulting safest and fastest route,

it was found that in 78% of the cases the trips were equal. This result is an important requirement for the sustainable safety principle were one is aiming at both safest routes and fastest routes. For the remaining 22% of the cases, there were differences between the fastest and safest routes. The travelled distance for the safest route was longer compared to the fastest route. The differences were caused by an increase of travelled distance on motorways and access roads. The FOT did not show a positive effect on the use of an incentive as was hypothesised. There are many possible causes that could have an influence on the result found. The main point was that both systems differed with respect to functionality and usability, e.g. the time to generate a safest route took significant longer compared to the calculation time for a fastest route.
In addition, due to various technological set-backs, the measuring period of the pilot was reduced several times. Because of the reduced measurement period, it is possible that an existing effect was not found.

The third study was performed to assess the probability that public authorities, automotive industry and insurance companies are going to apply certain deployment options to influence the user to buy Advanced Driver Assistance Systems (ADAS), and the probability that users will buy an ADAS given these deployment options.
To this end, an actor and user survey were held, using the stated preference methodology, to estimate models of actor and user decision making. To the actor survey, 75 reactions were received of which 72 were usable, and to the user survey 250 reactions were received. Three different Advanced Driver Assistance Systems (ADAS) were considered (for each of which it was expected that another actor would take the lead in deployment) and three deployment options were included for each actor (do nothing, stimulate or enforce). The different ADAS generally did not significantly influence the probability that actors will apply a certain deployment option.
The deployment options itself and to a lesser extent, the deployment options of other actors were most important for the probability that actors will apply deployment options. The probability that users choose to buy an ADAS was found to be highly dependent upon financial incentives.

In summary: A safest route algorithm is developed and implemented. This algorithm is successfully validated. In a survey drivers indicated a willingness to choose a safer route if a reward was given. Unfortunately, the field trial did not provide sufficient evidence that drivers actually drive this safer route. It is also uncertain whether the government or insurance companies are willing to provide incentives.

Contents

1 Introduction

In recent years, a number of studies and experiments have been conducted towards varying insurance premium. Around the world, a number of insurance companies have introduced such a policy, in which the amount of kilometres driven each year is the basis for the insurance premium. In the future, it could be expected that car owners will pay their insurance more and more by distance travelled. For professional drivers, no such policy is available yet. Especially for companies such as couriers, it is expensive to get a car insurance, because of the high risks for the insurance company. Varying the insurance premium per kilometre might not work for such companies because they already aim to reduce the amount of kilometres driven. Driving more means higher costs, and longer working hours for drivers, again increasing costs. A courier is thus less sensitive for a variable insurance premium per kilometre. However, current technology offers more options to make the insurance premium variable.

An insurance company aims at receiving enough premiums from its insured vehicles, while having as little claims as possible. Reducing the number of claims is thus profitable for the company, and should also be profitable for the customer. If the insurance company can influence the driving behaviour and choices of the customer, the premium could be reduced according to the changed behaviour. To control the behaviour of the customer, it is necessary to measure actual driving behaviour, including choices such as routes and time of travel. If the customer chooses to travel during periods and over routes which have a reduced risk of accidents, the insurance premium could be lowered. The same applies for someone who shows a safe driving behaviour. In other words, the customer pays the insurance premium that fits the driving behaviour.

In this study, we are interested in the effects of providing advice for the safest route to professional drivers. As an incentive to follow the advice, the insurance premium is made variable. The company, for which the driver works, could then receive a reward or incentive if his behaviour leads to a lower premium. In this project, incentive means any kind of stimulus for a company, planner or driver as a reward for good behaviour. The subject is to investigate the effects of a variable insurance premium and incentive structure on driving behaviour, costs, safety and traffic flow, when drivers are provided with feedback and advice. The general approach taken for this research is that of a pilot study for professional drivers. In the pilot study, a real life test (field operational test) will take place with the mentioned advice (for the safest route) and feedback on safe driving behaviour. It will also include the incentive structure to reward drivers and the variable insurance premium as incentive for the company as a whole.

The following problem definition was used.
Can an incentive be used to influence route choice and improve traffic flow, the cost and safety of professional drivers by providing advice and feedback?

To this end, Chapter 2 provides a literature overview on variable incentive structures. A conceptual model of the incentive program is proposed in Chapter 3. This model forms the basis for the incentive structure used in the remainder of this report. Chapter 4 describes a theoretical method to determine and assess routes with respect to safety. In order to assess drivers’ response to the incentives and thereby the potential benefit of safest routes, an online before-and-after survey was conducted. This study is described in Chapter 5. Chapter 6 describes the field operational test. This test uses the advice for the safest route and the incentive structure to reward drivers as discussed in previous chapters. This test comprises the main part of the project. The probability that stakeholders are going to take action in deployment of such systems is discussed in Chapter 7. Finally a discussion and integral conclusions (Chapter 8) are given.

2 Literature survey

The University of Twente provided the literature study presented in this chapter.
The professional pilot in the TRANSUMO project Intelligent Vehicles (IV) aimed at increasing safe driver behaviour by a variable insurance premium. The idea was to provide suggestions to drivers about the safest routes and safest driving behaviour. When a driver acts according to the suggestions, the insurance premium will be lower (STOK, 2007; TNO Inro, 2003).

Varying the insurance premium is not yet a common way to insure a vehicle. Only a few companies offer such an insurance policy (Norwich Union in the UK, Progressive Insurance in the USA, Holland Insurance in South-Africa and a few others (Victoria Transport Policy Institute, 2007; STOK, 2007)). Most of these insurance policies are based on a premium per kilometre drive and are also called Pay-As-You-Drive (PAYD) insurance policies. The premium of the insurance is, apart from certain risk characteristics such as age and region, based on the amount of kilometres driven.

A number of ideas are the basis for this type of car insurance (Victoria Transport Policy Institute, 2007; Litman, 2006a, 2006b; Guensler & Ogle, 2001). First of all, it is expected (based on price elasticity) that the amount of kilometres driven is reduced, because drivers have to pay for using a vehicle, while the insurance premium currently is paid up front. Through this reduction, most car owners reduce the cost of using their vehicle. The reduction also brings forward a reduction in external effects, such as accidents, congestion, emissions and use of car fuel. Another idea behind PAYD is that it leads to a fairer distribution of car ownership and car use, such that lower incomes also can afford to own a car.

Besides the advantages of PAYD, a number of critical annotations can be made (Victoria Transport Policy Institute, 2007; Litman, 2006a, 2006b; Guensler & Ogle, 2001). Most PAYD policies only use the amount of kilometres driven. Apart from this variable many other variables exist which also have a great influence on the probability of an accident, such as driving behaviour. These variables should also be taken into account. The possibility that the reduction in kilometres driven are the kilometres with the lowest probability of an accident also exists. The reduction then does not lead to a reduction in the number of accidents (or claims). The privacy of a driver is also worth some attention, especially when the driving behaviour is taken into account. As long as only the amount of kilometres driven is used, no problem exists with privacy, because this information is currently already registered with each annual vehicle inspection (APK).

From the existing literature, a number of notable items arise. First, the focus of all the studies is aimed at the private driver. Freight transport is not at all taken into account as a possible party of interest for a PAYD insurance policy. The results so far cannot easily be transferred to a professional environment, because the assessment of costs is different. After all, a private driver has to pay for the insurance himself, while a professional driver has the owner of the vehicle (other than the driver) paying for the insurance. Influencing the driving behaviour of a professional driver using a PAYD insurance thus is not obvious.

Second, most PAYD insurance policies are based on the amount of kilometres driven. The policy does not take into account in which way these kilometres are made, via which route, at what time of day or in what area. Mostly the existing criteria for risk groups are used, such as age and residence. If a GPS device is used, it would be possible to use these other variables as a basis for the PAYD insurance premium.

Third, all existing PAYD policies only aim at varying the insurance premium, actually targeting a reduction of the kilometres driven. This causes the chance of an accident happing to be reduced, causing fewer claims for the insurance company. No effort is made to influence the driving behaviour directly. Only the insurance premium varies. A driver only knows at the end of the month what his premium will be. With the aid of a personal navigation system, it would be possible to directly influence the driver, for example by advising the cheapest or safest route.

The existing literature shows some information on the effects of PAYD and the height of the insurance premium based on estimations (Victoria Transport Policy Institute, 2007; Litman, 2006a). For the USA, the premium would be 6 cents per mile on average, based on the current insurance premium and the current mileage. This premium would mean a reduction of driven miles of around 10%, based on price elasticity for car travel. For a number of regions in the USA a calculation was made what the effect would be with a premium of 2 cent per mile. That would lead to 4% less driven miles. In most cases, the premium is calculated using the current premium divided by the driven miles in a year. Someone with currently a low premium would get a low premium per mile, and based on price elasticity, would show only a small reduction in miles driven. A higher premium per mile would lead to higher reductions. On the basis of accident statistics it was estimated that a reduction of 10% in miles would lead to a reduction of 17% in accidents, because a vehicle itself has less change to cause an accident, but also gets less often involved in an accident caused by other vehicles.

To speedup the introduction of variable premiums, a market research was done in Minnesota, USA (Buckey et al., 2007). The research showed that only a small group is in itself interested in a variable premium, although they were interested in only paying for using a vehicle. The most important barrier that was mentioned is the uncertainty of the costs and the privacy. It also showed that most drivers have no idea of the price per kilometre of using a vehicle.

When looking at the utility of reducing the amount of miles driven, it shows that for each mile a utility can be found of around 16 cent, of which half is private and the other is public (Greenberg, 2007). This could be used to speedup the investments necessary to introduce PAYD insurance policies.

The relationship between route choice and safety is not often found in the available literature. Dijkstra et al., (2007) address this subject (the reader is referred to Chapter 4 for details). A Greek study (Yannis et al., 2005) shows that private drivers make a choice for a safer route on the basis of travel time related parameters. Costs are not important for choosing a safer route. This would mean that varying the premium using an advice for the safest route would not be very useful. Because the pilot aims at the professional driver, for whom costs play a very different role, it does deserve attention. Other important characteristics that play a role in choosing a safest route were gender, income and driving experience.

3 Conceptual model for the incentive program

Based on the introduction (Chapter 1) and the literature survey (Chapter 2), a conceptual model of the incentive program was developed by the University of Twente. This conceptual model was the basis for the model used in the on-line survey (Chapter 5) and the version as used in the Field Operational Test (Chapter 6).

Figure 1 shows the conceptual model. On the right side of the model, the human actors are depicted. These actors are:
- the driver,
- the planner,
- the haulier or entrepreneur,
- the insurance company.

The relation between these actors is made dynamic with a varying insurance premium. Because of the professional setting, the premium is not directly paid by the driver, but more likely by the owner of the company, or in other words the haulier or entrepreneur. This actor has to deal with both the driver and the planner, in order for the varying insurance premium to work. These two actors namely have a large influence on the route choice. This relation is depicted with the variable reward or incentive. For the insurance company and the haulier, it means an “improvement” of the service provided. This service can be individualized, allowing for a more sustainable approach and has some operational and financial advantages.

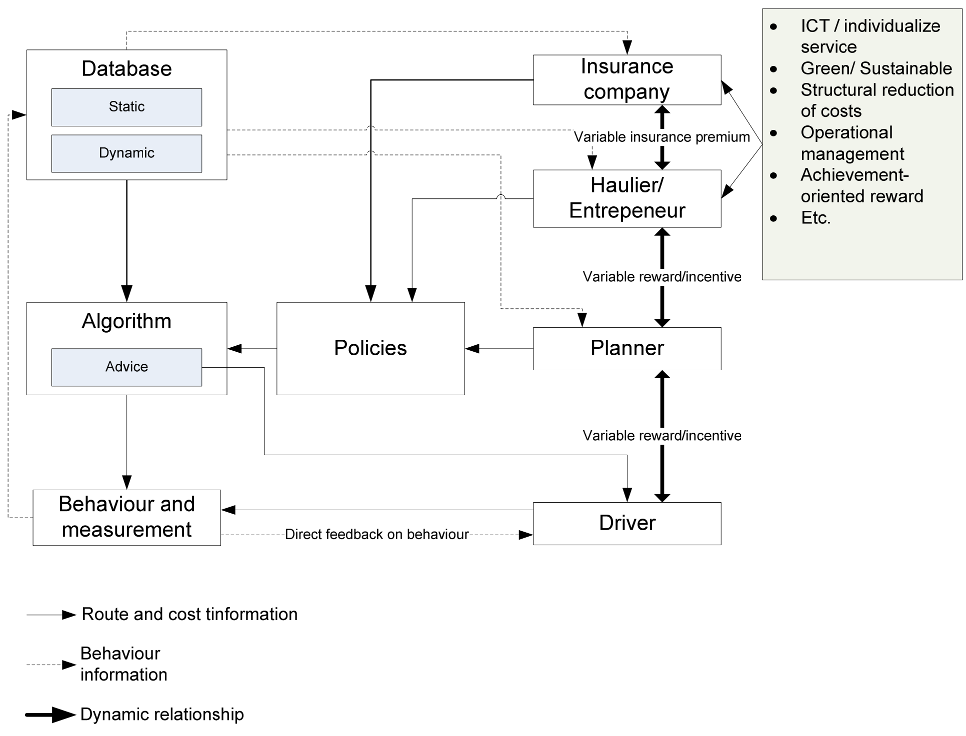


Figure 1 Conceptual model of the system.

The other elements in Figure 1 depict the actual system and its interfaces. Halfway is the insurance policy, or in other words the adjustable parameters, that are chosen. The insurance company, but also by the haulier and the planner, can adapt this policy because they have their influence on the running of the company. The policy determines the type of route guidance that is given, but also the incentives for the planner and driver.

The actual route guidance that is given to the driver is based on these adjustable parameters. The driver acts upon the advice, chooses routes, and shows his driving behaviour. Both the route choice and driving behaviour are measured. The driver receives direct feedback on both, and has knowledge of the effects on his reward. The measurements are also saved in a database which is available for all other actors, which allows them to act accordingly (adjust the parameters). The database consists of a static part, in which the map and other static characteristics (i.e. safety of routes) are stored. The dynamic part is used for all the measurements (i.e. driving behaviour, route chosen, etc.).

4 Methodologies for attaining safe routes and for safety evaluations

This chapter elaborated the safest route algorithm that was used in the Field Operational Test (Chapter 6). The algorithm is based on the theory of the 'Duurzaam Veilig Criteria' (Dijkstra & Drolenga, 2008). The professional pilot was the first attempt of implementing this algorithm for practical use.

Section 4.1 describes the algorithm. The resulting safety impact of a route choice can be assessed in various ways. Section 4.2 gives an overview of these assessment approaches. In Chapter 6, a simplified form of one these assessment approaches was used to determine the safety impact for a sequence of generated routes. The text in this chapter was contributed by the SWOV.

4.1 Methodology for attaining safe routes according to the Sustainable Safety policy

In the Netherlands, the concept 'Sustainably-Safe traffic' (Koornstra et al., 1992; Wegman & Aarts, 2005) is the leading vision in road safety policy and research. The main goal of a Sustainably-Safe road transport system is that only a fraction of the current, annual number of road accident casualties will remain (Section 4.2.6).

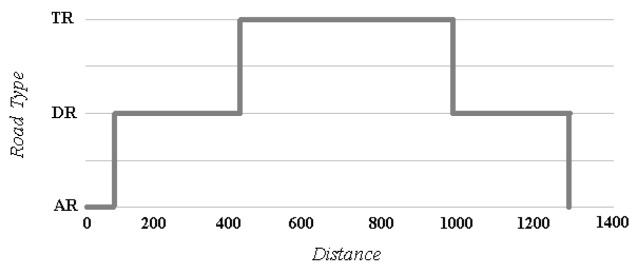
In a sustainable safe traffic system, an important requirement for road networks is that the quickest route should also be the safest route. This requirement can have the undesirable result that motor traffic would have to pass straight through residential areas (which usually have very safe roads and streets). There is therefore a supplementary requirement that a route must be structured in such a way that journeys may only start and end by travelling along the access roads, while the remainder (and biggest part) of the journey passes along through roads or, if these are not (adequately) available, along distributor roads . If such route choice is to be brought about in practice, the resistance (usually expressed in journey time) of a route straight through residential areas would have to be greater than that of a route via through roads and/or distributor roads. It is essential to a well functioning road network with sustainable safety that traffic is able to flow along through roads, otherwise the resistance of a route through residential areas will be seen as preferable to the resistance of a route via through roads.

The various (or most important) routes in a road network should comply with the for-mentioned requirements. For this reason, a theoretical framework was developed to determine the safety score of a route. This framework uses two methodologies: route diagrams and route stars.

4.1.1 Route diagrams

Using the lengths and categories of road sections that form part of a given route, a route diagram (Sustainable Safety Steps) can be constructed for each route. The progress of the route through the road categories in the network is compared to the distance.
The idea behind the route diagram is as follows: From a point of departure, cover the least possible distance via the lower road categories, via the right upward transition points (only one category per transition point), towards the highest road category in a road network, stay in that for as long as possible and then follow the correct downward transitions (one category per transition point) via the least possible distance along the

lower road categories until the destination is reached. An example of a route diagram is shown in Figure 2.



AR = Access Road, DR =Distributor and TR = Through Road

Figure 2 Route diagram for an arbitrary route.

Route diagrams provide a visual impression of the Sustainable Safety character of a route. As soon as we start comparing routes, the shortcomings of this visual representation become apparent. To get a quantitative assessment, we allocate a score to each route based on nine criteria, see Table 1. The authors drew up these criteria based on general knowledge of risks to road safety (Dijkstra et al., 2007). These criteria are all of a quantitative type and have the same 'direction': the lower the score for a criterion, the greater the road safety. In the following, we shall explain the nine criteria, one by one.

Number of transitions between road categories limited
An optimum route diagram has the right number of category transitions. In a network containing N number of road categories, a route should have a maximum of (N-1) upward transitions between categories and a maximum of (N-1) downward transitions between categories. An excessive number of transitions should incur a penalty, which can be expressed in the formula:

$$\begin{array}{llll} \text{If} & O \leq (2N-2) & \text{then} & EO = 0 \\ \text{If} & O > (2N-2) & \text{then} & EO = 2 + O - 2N \end{array}$$

in which O is the total number of category transitions in the route in question, N is the number of road categories in the network and EO is the number of extra transitions.

Nature of the transition is correct (not more than one step at a time)
It is important to make a distinction between upward and downward transitions.
An upward transition involves moving to a higher category, a downward transition involves moving to a lower category. By considering the difference between the categories, the correctness of the transition can be assessed. The nature of the transition is calculated as follows:

$$AO = \left| C_j - C_i \right|$$

in which AO is the nature of the transition and Cj is the next category after the category Ci under consideration.

A category transition fulfils the second requirement if AO = 1. If AO > 1, the category transition does not meet the requirement. The number of faulty category transitions in a route is counted in this way.

As few missing road categories as possible
The number of road categories encountered in a route, in relationship to the number of road categories present in the network, forms the fourth requirement. This can be expressed in the formula

$$OWC = WCN - WCR$$

in which OWC is the number of missing road categories, WCN is the number of road categories present in the network and WCR is the number of road categories encountered in the route under consideration.

Proportion (in length) of access roads as low as possible
From a road-safety viewpoint, through traffic in 30 km/h (20 mph.) zones should be avoided. The proportion, in length, of access roads ALETW in relation to the total length LTOT is calculated as follows:

$$AL_{ETW} = \frac{L_{ETW}}{L_{TOT}} \times 100\%$$

Proportion (in length) of distributor roads as low as possible
Distributor roads are the least safe when it comes to the risk of accidents. For that reason, the ratio in length of these roads should be kept as low as possible.
The proportion, in length, of distributor roads ALGOW in relation to the total length LTOT is calculated as follows:

$$AL_{GOW} = \frac{L_{GOW}}{L_{TOT}} \times 100\%$$

Travel distance
The smaller the total distance LTOT travelled on a route, the less risk to which a vehicle is exposed. The total distance LTOT is equal to the sum of the distance over access roads LETW, the distance over distributor roads LGOW and the distance over through roads LSW. This is expressed as the formula

$$L_{TOT} = L_{ETW} + L_{GOW} + L_{SW}$$

Travel time
The total travel time R is calculated for each route on the basis of an empty network. This is done by totalling the length of the categories divided by their respective speed limits, expressed by the formula

$$R = \frac{L_{ETW}}{V_{ETW}} + \frac{L_{GOW}}{V_{GOW}} + \frac{L_{SW}}{V_{SW}}$$

As few turnings as possible across oncoming traffic
The number of left turns (LAB) at junctions can be recorded for each route. Because turning left is seen as the most dangerous manoeuvre (Drolenga, 2005), the score declines as the number of these movements increases.

Low junction density on distributor road
The purpose of this requirement is to assess the route's potential for disruption on the distributor roads within it. The junction density KPD is defined as the number of junctions on distributor roads K per km of distributor road. This is expressed as the formula

$$KPD = \frac{K}{L_{GOW}}$$

Nine criteria summarised
The nine criteria including their dimensions are shown in Table 1. Some of these criteria are related to each other. For instance, travel distance is related to travel time in an 'empty' network. As soon as the network is saturated, this relationship will disappear. The proportion of a certain road category and travel distance seem to be mutually dependent, however, two routes having the same length of access roads will have different proportions of access roads when the total travel distances of both routes differ.

Table 1 Nine criteria for route diagrams.

Criterion	Description	Unit
1	Number of transitions	Number of additional transitions
2	Nature of transitions	Number of wrong transitions
3	Missing road categories	Number of missing categories
4	Proportion of access roads	Percentage of total distance
5	Proportion of distributors	Percentage of total distance
6	Travel distance	Meters
7	Travel time	Seconds
8	Left turns	Number of left turns
9	Junction density	Number of junctions per kilometre

4.1.2 Route starts
For each route we can calculate the scores for the nine aforementioned criteria by collecting the data and applying the formulae. Using a multi-criteria analysis, we then try to arrange alternative routes in order of preference. Standardisation of the criterion scores is necessary if the different scores of the various routes are to be compared.
The scores are standardised on the basis of interval standardisation. This means that the best alternative is awarded a score of 0, the worst a score of 1, and the other options are scaled between 0 and 1. This is done by reducing the score by the lowest score for the criterion in question and dividing this difference by the difference between the maximum score and the minimum score for the criterion in question. This is expressed as the formula

$$G_{ji} = \frac{C_{ji} - min_j\{C_{ji}\}}{max_j\{C_{ji}\} - min_j\{C_{ji}\}}$$

in which Gji is the standardised score of alternative i for criterion j and Cji is the criterion score of alternative i for criterion j.

In determining the minimum and maximum scores for a criterion, not only the routes that are actually followed should be taken into account, but also the routes that are not followed but are nevertheless available in the infrastructure.

Routes can easily be compared by using stars to visually represent the standardised scores for the nine criteria. The nine points of a star represent the nine criteria.
Each point shows '1 - Gji ': the longer a point, the better the score for this route is in relationship to alternative routes. This means that the more complete the star is the more sustainable safe the route is. The scores for the nine criteria on two routes are shown as an example in Figure 3.

Figure 3 Route starts for two arbitrary routes.

The left-hand route (purple star) has the worst score for the first requirement (the number of additional transitions) because no point, or only part of a point, is visible. By contrast, the right-hand route (green star) has the best score for this requirement because the entire point is visible. Because the green star is more complete than the purple star, it may be concluded that the right-hand route fulfils the requirements of the Sustainable Safety policy more than the left-hand route.

Criteria weights
After the scores have been standardised, the weighting of the criteria can be determined. If each criterion is chosen to be of equal importance, then each of them counts with the same weight. If one or more criteria are considered more important, these may be allocated a greater weight than less important criteria. The sum of the weights of the criteria must always come to 1, so if all nine criteria are considered of equal importance, each criterion is given a weight of 1/9.

Total score for a route
To arrive at a total score for each route, the standardised score is multiplied by the weight and added up over the nine criteria to give total scores (weighted totalling method). The outcome of this total score indicates the degree of unsafety. To arrive at a safety score, the unsafety score is deducted from 1 and multiplied by 100% so that the safety score will fall between 0 and 100%. This is expressed as the formula

$$VV_r = 100 - 100 \times \sum_{c=1}^{C} ss_c \times g_c$$

in which VVr is the safety score of route r, C is the number of criteria, ssc is the standardised score for criterion c and gc is the weight of criterion c.

4.2 Relevant methodologies for assessing road safety

This subsection is partially taken from Dijkstra et al., 2008.

Road safety can be assessed in different ways. The most direct way is represented by the crash statistics. It is possible to derive all kinds of risk figures from these crash statistics by combining the number of crashes with the road length or the amount of traffic on a road (type).

However, crash statistics are only available for existing roads and existing situations. For new roads and for new types of (counter)measures (e.g. ADAS) the safety level or the safety effects can not be assessed by crash figures. Instead, other safety indicators need to be used. One option is to use models which 'predict' the number of crashes given the characteristics of a road (type) or the amount of traffic to be expected. Other safety indicators are based on more indirect measures such as the number of conflicts calculated by a microscopic simulation model.

A third type of safety indicators is generated by expert knowledge, e.g. a road safety auditor who assesses the safety of a new design by using his experience.

4.2.1 Crash data

Crash data are the most direct way of indicating both the nature of the safety problem and the level of safety. Many tools have been developed for selecting, structuring, analyzing, and visualizing crash data. These tools are useful for existing situations and for existing roads. The nature of crash statistics is that it shows the safety of the past. As soon as one is planning new roads, new types of technical equipment for vehicles, new road facilities, these statistics are of no use anymore. Other indicators are needed for analysing future situations.

4.2.2 Key safety indicators

Key safety indicators quantify the safety of certain types of roads and junctions. A key safety indicator is determined by relating the absolute level of unsafety (e.g. the number of crashes) on a certain type of road or junction to the degree of exposure.

Janssen (1988, 1994) gives a general expression for calculating a key safety indicator:

$$Key\ safety\ indicator = \frac{Safety\ level}{Degree\ of\ \ Exposure}$$

The safety level is frequently quantified by using crash records. The number of vehicles or the number of vehicle/kilometres is often used to calculate the degree of exposure.

An example of a key safety indicator is the number of accidents involving injury per million vehicle kilometres driven. This key safety indicator is also referred to as the risk of a road or junction type. The risk (indicator) based on vehicle kilometres takes into account not only the number of accidents but also the road length and the number of motor vehicles that pass along it (Janssen, 2005).

By combining the length of the road section with the intensity, we can calculate the level of exposure, expressed in millions of vehicle kilometres driven in a year. The level of exposure is then calculated as follows:

$$VP_i = L_i * I_i * 3{,}65.10^{-4}$$

in which VP_i is the level of exposure of road section i in millions of vehicle kilometres driven in one year, L_i is the length of the road section i in km and I_i is the daily volume for road section i.

Then, by multiplying the level of exposure VP_i by the associated key indicator K_i, the expected number of injury crashes LO_i on road section i can be estimated.

$$LO_i = K_i * VP_i$$

The key indicator K for road section i depends on the type of road. The key indicators used here for access roads (speed limit 30 or 60 km/h), distributor roads (50 or 80 km/h) and through roads (100 or 120 km/h) are shown in Table 2.

Table 2 Key safety indicators for road types characterised by speed limit (edited version of Janssen, 2005; p. 46).

Road with speed limit in km/h	Key indicators in number of crashes with serious injury, per billion motor vehicle kilometres
120	26
100	48
80	148
60	287
50	422
30	293
Netherlands	167

By totalling the calculated, expected injury crashes on the road sections that form part of a route, the total expected injury crashes on the route in question can be derived.

4.2.3 *Crash Prediction Models*

Crash Prediction Models are another way of indicating road safety. Using Average Daily Traffic and road characteristics as an input, the number of crashes or casualties can be calculated (FHWA, 2000, 2005; Reurings et al., 2006).

The general expression for a crash prediction model is:

$$\mu_i = \alpha \cdot AADT_i^{\beta} \cdot e^{\gamma_j \cdot x_{ij}},$$

where μ_i is the expected number of crashes in a certain period, $AADT_i$ is the Annual Average Daily Traffic in the same period, x_{ij} are other explanatory variables, α, β, γ_j are the parameters to be estimated and the subscript i denotes the value of a variable for the i-th road section.

Reurings et al. (2006) conclude that (for main roads) the other explanatory variables should at least include the section length, the number of exits, the carriageway width, and the shoulder width.

4.2.4 *Traffic conflicts*

Road safety on the level of road sections and junctions is mostly expressed by the number of crashes. However, the number of crashes for a separate road section or junctions is mostly too small for an in-depth analysis to be performed. The number of traffic conflicts and near-crashes is much higher, therefore enhancing the possibilities for analyses. Studying conflicts and near-crashes presumes a relationship between a conflict and a 'real' crash. This relationship was studied extensively by Hydén (1987) and Svensson (1998).

The assumption for using this method is that situations with many conflicts have a higher probability for accidents. Trained observers regard traffic situations and analyse and count ´conflicts´. Conflicts are actions of road users, which may lead to problems (e.g. late braking, cutting of bends) and which appear often enough. Several measurements have been proposed to characterize traffic conflicts in detail. For example time to collision (TTC), deceleration rate (DR), encroachment time (ET), post encroachment time (PET), etc. are used to determine the severity of a traffic conflict objectively. This technique enlarges the amount of data but the used parameters resulting from the manoeuvres are not necessarily direct indicators for risk of accident and reduction of severity.

4.2.5 *Surrogate safety measures*

When using a microscopic model conflicts between vehicles will be an integral part of the simulation. The outcome will be used to compare the types of conflicts in a given simulation with the types of conflicts, which will be 'acceptable' in a Sustainable-Safe road environment, e.g. conflicts with opposing vehicles should be minimised at high speed differentials.

Time To Collision (TTC) (Van der Horst, 1990) is an indicator for the seriousness of a traffic conflict. A traffic conflict is defined by FHWA (2003) as ‘an observable situation in which two or more road users approach each other in time and space to such an extent that there is a risk of collision if their movements remain unchanged’.
The TTC value differs between junctions and road sections. A TTC on road sections will be relevant when one vehicle is following another one or when there is oncoming traffic. A vehicle on a road section can only have one minimal TTC value. A TTC value on junctions relates to vehicles approaching each other on two different links. A vehicle approaching a junction can have more than one minimal TTC value, depending on the number of vehicles on the other links.

Minderhoud and Bovy (2001) have developed two indicators that can be applied in micro simulations and are based on the TTC: the Time Exposed TTC (TExT) and the Time Integrated TTC (TInT). The TExT expresses the duration that the TTC of a vehicle has been below a critical value - TTC* - during a particular period of time. The TExT is thus the sum of the moments that a vehicle has a TTC below the TTC*. That means that the smaller the TExT, the shorter time a vehicle is involved in a conflict situation, and therefore, how much safer the traffic situation is. The TExT indicator does not express the extent to which TTC values occur that are lower than the critical value. In order to include the impact of the TTC value, the TInT indicator has been developed. This is the area between TTC* and the TTC that occurs.

Another way to express the impact of a conflict is to calculate the potential collision energy (PCE) that is released when the vehicles are in conflict and collide with each other. Masses and speeds of the vehicles, as well as the way in which the vehicles collide with each other, i.e. the conflict type, influence the potential collision energy.

4.2.6 Comparing design features with design requirements

In the Netherlands, the concept 'Sustainably-Safe traffic' (Koornstra et al., 1992; Wegman & Aarts, 2005) is the leading vision in road safety policy and research.
The main goal of a Sustainably-Safe road transport system is that only a fraction of the current, annual number of road accident casualties will remain.

It is of great importance for a Sustainably-Safe traffic system that, for each of the different road categories, road users know what behaviour is required of them and that they may expect from other road users. Their expectations should be supported by optimising the recognition of the road categories.
The three main principles in a Sustainably-Safe traffic system are:

- functionality,
- homogeneity,
- recognition/predictability.

The functionality of the traffic system is important to ensure that the actual use of the roads is in accordance with the intended use. This principle led to a road network with only three categories: through roads, distributor roads, and access roads. Each road or street may only have one function; for example, a distributor road may not have any direct dwelling access. The speed limit is an important characteristic of each road category: access roads have low speed limits (30 km/h in urban areas and 60 km/h in rural areas) while through roads has a speed limit of 100 or 120 km/h.

The homogeneity is intended to avoid large speed, direction, and mass differences by separating traffic types and, if that is not possible or desirable, by making motorised traffic drive slowly.

The third principle is that of the predictability of traffic situations. The design of the road and its environment should promote the recognition, and therefore the predictability, of any possible occurring traffic situations.

These principles have been translated into safety design requirements, for instance:
For road sections

- Avoiding conflicts with oncoming traffic,
- Avoiding conflicts with crossing traffic,
- Separating different vehicle types,
- Avoiding obstacles along the carriageway.

For junctions

- Avoiding conflicts with crossing traffic,
- Reducing speed,
- Limiting the number of different traffic facilities.

Design requirements in general, which are part of design manuals, are not only based on safety arguments but also on other arguments, like capacity and liveability. In addition, a designer will apply the requirements given the constraints in a real-life situation.

Therefore, Van der Kooi & Dijkstra (2000) suggested a test to find out the differences between the original safety requirements and the characteristics of the actual design features. This SuSa test systematically compares each design element or feature with the relevant safety requirements. As a result a percentage shows the total score on Sustainable Safety.

5 Cost-benefit analysis and the results from an empirical study

In order to assess drivers' response to the incentives and thereby the potential benefit of safe routes, an online before-and-after survey was conducted. In total 45 Dutch professional drivers participated in the survey. The results showed that drivers tend to ignore safety-related information in making their route choices; however, the incentives had some significant effects on these choices. The incentives therefore present an efficient way of influencing drivers' route choices. The text in this chapter was also presented in Bie, van Arem, & Igamberdiev (2010).

5.1 Introduction

Traffic safety depends on three major factors: the road infrastructure, the quality and safety level of vehicles, and the behaviour of drivers (Kumara and Chin, 1897; Kononov et al., 2008; van der Horst, R., and de Ridder, 2007). Many projects and programs have been initiated by both government and industry to improve traffic safety (Masliah, Bahar and Parkhill, 2004; Wegman, Dijkstra, Schermers, and Vliet, 2006; Shen and Gan, 2003; Sheikh, Alberson, and Bullard, 2005). An efficient way (in terms of the cost involved and the time scale) for traffic safety enhancement is to promote safe driving behaviour. Many studies have explored the potential factors that may influence driver behaviour and contribute to traffic safety improvement *(*van der Horst, R. and de Ridder, 2007; MacCarley, 2005; Lundgren, and Tapani, 2006). The methods used for safety enhancement can be grouped into the following two categories:

1 The microscopic approach (Tideman, van der Voort, van Arem, and Tillema, 2007; van Driel, Hoedemaeker, and van Arem, 2007; van Driel, and van Arem, 2008) looks at individual drivers and vehicles. It may assist the driver in the manoeuvre of the vehicle, such as speed maintenance, lane keeping and steering control. It can also help avoid collisions between vehicles and between vehicle and road-side objects or pedestrians, by enabling communication and better cooperation between the vehicles (V2V) and/or between the vehicle and the infrastructure (V2I).
2 The macroscopic approach looks at the network level of traffic flows. By controlling the distribution of traffic flow among the network, high safety may be achieved.

The macroscopic approach can be further divided into the following categories, based on how network flow control is carried out:

- demand management,
- temporal distribution management, and
- spatial distribution management.

Road pricing, although aimed to mitigate congestion, reduces travel demand and as a result may also improve traffic safety (Jones and Hervik, 1992; Eliasson, 2009). Temporal management involves the dispersion of traffic demand over time, such as peak hour restriction strategies. A Dutch practical test on rewarding drivers for peak hour avoidance shows that positive incentives are able to reduce the amount of peak traffic by 60-65% (Ettema, 2008; Ben-Elia, and Ettema, 2009). Spatial management deals with the dispersion of the traffic demand over the road network (i.e. traffic assignment). In this study we were especially interested in the effect of drivers' route choice on traffic safety, since different routes have different safety levels (Chapter 4;

Dijkstra, Drolenga, and van Maarseveen, 2007). In particular, we will investigate the effect of using economic incentives to influence drivers' route choices.

Interventions in drivers' decision making process are realized by either enforcement or (positive) incentives. Enforcement normally involves legislation, such as speed limit and the prohibited use of hand-held mobile phones while driving. Drivers are punished (by warning, fine, or imprisonment) if they fail to comply with the prescribed rules. On the other hand, incentives, known as "soft measures", provide an extrinsic motivation for drivers to follow these rules, as doing so would bring them certain rewards.

Research on using incentives to promote safe driving includes studies on safety belt use in the United States (Johnston, Hendricks, and Fike, 1994; Hagenzieker, Bijleveld, and Davidse, 1997) as well as in the Netherlands (Hagenzieker*, 1989;* Hagenzieker *1991).* Incentive campaigns were shown to substantially stimulate safety belt use, with a short-term increase of 12 percentage points in average. Safety belt use dropped after withdrawal of the incentive campaigns but was generally still higher than initial baselines. A Dutch practical test on rewarding drivers for speed and headway keeping (Belonitor, 2005) and a Dutch pilot program on rewarding drivers for peak avoidance (Ettema, 2008; Ben-Elia, and Ettema, 2009) showed similar results, observing considerable behavioural adaptation during the test but little remnant effects after the test. Another area of research focuses on using incentives to influence the decision to drive: the Pay-As-You-Drive (PAYD) insurance policy (Litman, 2008; Vonk, Janse, van Essen, and Dings, 2003). In PAYD, the insurance premium is not fixed but based directly on the actual distance driven. Drivers then have an incentive to reduce vehicle use; as a result the number of traffic accidents can be reduced by up to 5.7% (Zantema, van Amelsfort, Bliemer, Bovy, 2008).

An important factor for accident exposure, besides vehicle manoeuvre and the driven distance, is the selection of routes between origins and destinations. Different routes have different characteristics in terms of road types, speed, congestion level and so on, all contributing to the safety level of the trip (Chapter 4; Dijkstra, Drolenga, and van Maarseveen, 2007; Dijkstra, and Drolenga, 2008). Freeways are the safest type of roads (on average 0.06~0.08 accidents per million vehicle kilometers), compared to interurban roads (0.22~0.43) and urban roads (0.57~1.10). If incentives are provided for drivers to follow "safe routes", we could expect a decrease in traffic accident. To study the potential benefit of such an incentive program, three interrelated subjects need to be addressed:

1. architecture of the incentive program, i.e. selection of the "reward routes" and design of the incentive structure (types and values of reward) (Bie and van Arem, 2009),
2. drivers' behavioural adaptation in terms of route choice, in response to the incentive program,
3. traffic impact as a direct result of drivers' adapted behaviour, such as effects on traffic accident occurrence (rates and severity).

In this empirical study, we focussed on drivers' reaction to the incentive program and the resulting impact on the program operators, i.e. the subjects (2) and (3). We considered the operation of the incentive program to be lead by a logistic company, who pays for insurance of its fleet and employs professional drivers to drive the vehicles.
The insurance company offers a variable premium scheme, were discounts are made

according to the compliance ratio with the safe routes. The logistic company then decides the amount of incentives to be paid to drivers who have followed the safest routes. This chapter is organized as follows: Section 2 introduces the theoretical framework of the incentive program. The variable insurance premium scheme and the incentive structure are formulated, as well as drivers' route choice behaviour. In Section 3, cost-benefit analyses are conducted for the individual drivers and for the two operating companies. This is followed by the optimization problem of the incentive program. Section 4 includes the description and data analysis of an online survey, which was designed to investigate driver response to the incentive program. Finally, Section 5 concludes with some discussions on future research topics.

5.2 Theoretical Framework of the Incentive Program

We consider in this empirical study the incentive program to be operated with an incentive structure and a variable premium scheme (see also Chapter 3). Three players are involved here: an insurance company, a logistic company, and the professional drivers. The insurance company offers a variable insurance premium to the vehicles owned by the logistic company. Different to traditional insurance packages of fixed premium, the premium here varies according to the safety performance of the drivers. To make this operational, the insurance company provides certain safety instructions and the premium is dependent on how the instructions are followed. In our case, these safety instructions are realized by presenting to the drivers the safest route for their trip and the insurance premium is discounted if drivers comply with these instructions.

The logistic company employs professional drivers to drive the vehicles. In order to encourage the drivers to follow the safest route guidance, the logistic company offers an incentive structure which rewards the drivers if they follow the guidance. The drivers then decide whether they will follow the route as they normally do, or switch to the safest route for which they would receive a reward (i.e. the incentive). Figure 4 provides a general overview of the operational scheme of the incentive program. An on-board unit (OBU) is equipped on the vehicle with an embedded navigation system. It displays the safest route and the amount of route incentives to the drivers; on the other hand, it records drivers' actual route choice and then calculate whether the driver followed the safest route or not and the amount of incentives the driver is eligible for.

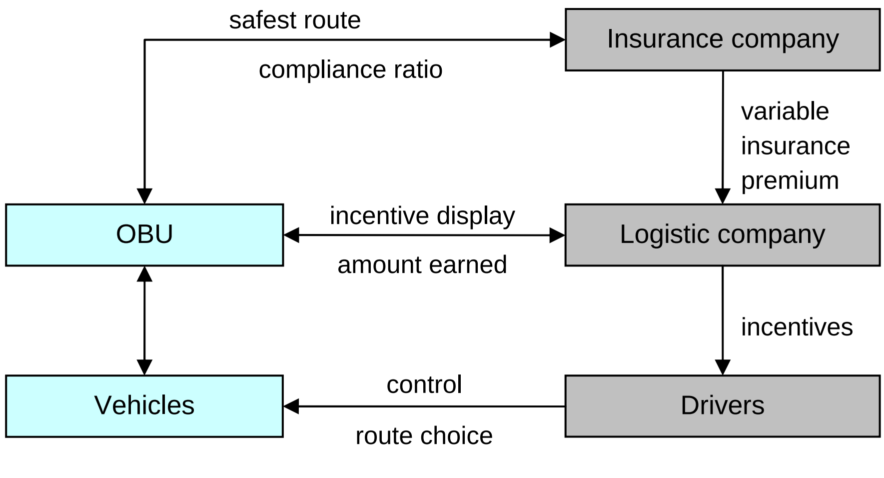


Figure 4 Operational framework of the incentive program.

5.3 The Variable Insurance Premium Scheme

Consider the N vehicles owned by the logistic company. It is assumed that each vehicle is only driven by a designated driver. The vehicles, as well as the drivers, can then be numerated as $1, 2, ..., N$. For each vehicle, the annual insurance premium for a vehicle is dependent on its annual mileage and the percentage of the safest route being followed. This can be expressed as

$$v_i = f(M_i, \gamma_i), \tag{1}$$

where v_i is the premium to be paid for vehicle i, M_i is the expected annual mileage for the vehicle, and γ_i is the percentage at which the safest route is followed. The more frequently the safest route is followed, the lower the premium is. If a linear discount rate is applied, (1) is transformed to

$$v_i = v_{Mi} - \rho_i \gamma_i. \tag{2}$$

Here ρ_i ($0 < \rho_i < v_{Mi}$) represents the reduced amount in insurance premium for the case of $\gamma_i = 1$. That is, if the safest route is followed all the time, then the insurance to be paid is $v_{Mi} - \rho_i$. If the safest route is followed less frequently, the insurance to be paid will be some amount between $v_{Mi} - \rho_i$ and v_{Mi}.

The total amount of premiums that the insurance company will receive from the logistic company is then given as

$$V = \sum_{i=1}^{N} v_i = \sum_{i=1}^{N} \left(v_{Mi} - \rho_i \gamma_i \right). \tag{3}$$

If the premiums are fixed rather than variable, v_{Mi} is the amount to be paid for vehicle i. The total amount is then

$$V_0 = \sum_{i=1}^{N} v_{Mi}. \tag{4}$$

The difference between (3) and (4), i.e. $V_0 - V$, is the reduced amount of insurance premiums paid by the logistic company to the insurance company. This difference is caused by the variable premium scheme. In terms of cost-benefit analysis, this amount accounts as a loss to the insurance company but a gain for the logistic company.

5.4 The Incentive Structure

The logistic company pays incentives to its drivers in order to encourage them to take up the safest routes when making their trips. For each trip, the safest route is determined by the insurance company and made known to drivers for each OD trip. This safest route might be different from the route that the driver would normally take when making the trip. The incentive then works as a stimulus for the drivers to switch to the safest route.

For an OD trip j made by driver i, denote b_{ij} as the amount of incentive awarded to the driver if they follow the safest route. If the probability that the driver will indeed

follow this route is given by p_{ij}, then the expected amount of eventual incentive payout for this trip is $p_{ij}b_{ij}$. Denote J_i as the total number of trip per year for vehicle i.
The compliance ratio γ_i can be estimated by

$$\gamma_i = \frac{\sum_{j=1}^{J_i} p_{ij}}{J_i}. \tag{5}$$

The expected total amount of incentives paid out by the logistic company to the drivers is then given as

$$B = \sum_{i=1}^{N}\sum_{j=1}^{J_i} p_{ij}b_{ij}. \tag{6}$$

5.4.1 *Drivers' Route Choice Behaviour*

Random utility theory is applied to model drivers' route choice behaviour. The logit model is adopted: when making OD trip j, the probability for an individual driver i to choose route r out of the available route set $\mathbf{R}_j = \{1, 2, ..., m_j\}$ is given by

$$p_{ijr} = \frac{e^{\theta u_r}}{\sum_{s=1}^{m_j} e^{\theta u_s}}. \tag{7}$$

Here u_r represents the utility of route r when making the OD trip j, and θ is a dispersion parameter related to the driver's perception precision of the utilities on different routes.

Utility describes how desirable a route is and is formulated as a linear-in-form function of the route attributes:

$$u_r = \beta_1 t_r + \beta_2 c_r + \beta_3 k_r + \beta_4 b_r, \tag{8}$$

where t_r is the travel time on route r, c_r is the fuel cost (and also any payable toll charge) along route r, k_r is a safety measure of route r, and b_r as introduced in Section 2.2 is the amount of incentive applicable to route r.

It can be argued that fuel cost does not concern the driver because in most of the cases the logistic company will cover such cost. However, we keep fuel cost as a component of the utility function for consistency with other studies. When drivers do not pay the fuel cost themselves, we can expect the value of β_2 in (8) to approach 0.

The safety component in (8) is included to see whether drivers take safety into account even without incentives. It is also interesting to check whether the incentive structure will have some "training" effect on the drivers' route choice behaviour, i.e. whether the incentive structure will raise drivers' awareness on route safety. This can be verified via an ABA sequential study were A represents the case were no incentive structure is implemented and B presents the case were the incentive structure is implemented.
By observing drivers' behaviour through the different phases we may identify different behavioural patterns in the two A phases; this difference can be attributed to the temporary implementation of the incentive structure.

5.5 Evaluation and Optimization of the Incentive Program

The impact of the incentive structure and the variable premium scheme is analyzed here. For the incentive program to be acceptable, it has to bring benefit to all players in the game. Cost benefit analysis is made for the three players: the drivers, the logistic company, and the insurance company. Furthermore, optimization of the program in order to minimize/maximize cost/benefit is also discussed.

5.5.1 Cost-Benefit Analysis for the Drivers

We assume that the drivers/vehicles participating in this incentive scheme only contribute to a very small amount of the total traffic flow in the network. And the incentive scheme changes only these drivers' behaviour but not other drivers' behaviour. It is then reasonable to assert that the changes of traffic conditions in the network with and without the incentive structure are negligible. The attributes of the routes remains the same after the implementation of the incentive structure, except that the safest routes have now an added utility of the incentive.

The effect of the incentive structure on the cost-benefit of the drivers is analyzed below for all possible cases.

1. If the incentive is rewarded to the route that the driver normally chooses, then, after the implementation of the incentive structure, the drivers enjoys a gain equivalent to the amount of the incentive paid.
2. If the incentive is rewarded to a route that the driver does not normally choose, then: (a) if the new utility on the guided route, inclusive of the incentive, is higher than that of the normal route, the driver switches to the guided route and gains the difference of the utilities of the two routes; or (b) if the new utility on the guided route, inclusive of the incentive, is still lower than the utility of the normal route, then the driver stays on the normal route. This way the driver has no gain, neither any loss.

Drivers are then never at a loss because of the incentive structure. Therefore, the implementation of the incentive structure is always beneficial to the drivers and they will welcome such a program.

5.5.2 Cost-Benefit Analysis for the Logistic Company

The logistic company plays the middle role in the game. It has interactions with both the insurance company and the drivers it employed. The logistic company pays the insurance premiums to the insurance company and it also offers the incentives for the drivers to follow the safety instructions. Compared to the traditional case of fixed premium, the logistic company pays less to insurance company but it also has to pay the additional cost of the incentives.

The logistic company's net benefit from the incentive program can be expressed as

$$Q_{LC} = V_0 - V - B. \qquad (9)$$

If this amount is positive then the logistic company is at gain and benefits from the implementation of the incentive program. Further expanding the equation we have

$$Q_{LC} = \sum_{i=1}^{N} v_{Mi} - \sum_{i=1}^{N} \left(v_{Mi} - \rho_i \gamma_i \right) - \sum_{i=1}^{N} \sum_{j=1}^{J_i} p_{ij} b_{ij} = \sum_{i=1}^{N} \rho_i \gamma_i - \sum_{i=1}^{N} \sum_{j=1}^{J_i} p_{ij} b_{ij}$$
$$= \sum_{i=1}^{N} \rho_i \frac{\sum_{j=1}^{J_i} p_{ij}}{J_i} - \sum_{i=1}^{N} \sum_{j=1}^{J_i} p_{ij} b_{ij} = \sum_{i=1}^{N} \sum_{j=1}^{J_i} \left(\frac{\rho_i}{J_i} - b_{ij} \right) p_{ij}. \tag{10}$$

In (10), ρ_i is determined by the insurance company; the logistic company decides on b_{ij} which subsequently affect p_{ij} and γ_i. We can see that as long as $b_{ij} < \frac{\rho_i}{J_i}$ is assured for all i, j then $Q_{LC} > 0$. This means that the amount of the incentives should not be too much; otherwise the logistic company would suffer a financial loss.

5.5.3 *Cost-Benefit Analysis for the Insurance Company*

The insurance company's profit is determined by revenue minus cost. Revenue comes from the collected premiums and cost goes for the accident claims which the insurance company has to pay out. The company gains if the decrease in claim pay-outs is bigger than the reduction of collected premiums. The company loses if the claim pay-outs does not decrease or decreases less than the reduced premiums.

The reduction in collected premiums is given by

$$\Delta V = V_0 - V = \sum_{i=1}^{N} \rho_i \gamma_i. \tag{11}$$

The reduction in claim pay-out has to be estimated based on the different route safety levels. The expected accident cost for travelling along a route can be said to be directly related to the safety measure of the route. Here, by using accident cost instead of accident number, we have taken into account both accident occurrence and accident severity. If a linear relationship is assumed, then for vehicle i to make OD trip j along route r, the expected accident cost can be said to be $\lambda\left(\kappa - k_r\right)$; here $\kappa - k_r$ gives a measure on route "unsafety" and λ is the linear coefficient. The total expect accident cost, which will be recovered by insurance pay-out, is then sum as

$$K = \sum_{i=1}^{N} \sum_{j=1}^{J_i} \sum_{r=1}^{m_j} \lambda\left(\kappa - k_r\right) p_{ijr}. \tag{12}$$

Compare with the before period were no incentive structure was implemented, the same formula can be applied to estimate the total accident cost. The only difference lies in the different route choice probabilities. Taking $b_r = 0$ into (8) and then into (7) and then into (12) we have

$$u_r^{(0)} = \beta_1 t_r + \beta_2 c_r + \beta_3 k_r, \tag{13}$$

$$p_{ijr}^{(0)} = \frac{e^{\theta u_r^{(0)}}}{\sum_{s=1}^{m_j} e^{\theta u_s^{(0)}}}, \tag{14}$$

$$K_0 = \sum_{i=1}^{N} \sum_{j=1}^{J_i} \sum_{r=1}^{m_j} \lambda \left(\kappa - k_r \right) p_{ijr}^{(0)}. \quad (15)$$

The reduction in accident pay-out is then given by

$$\Delta K = K_0 - K. \quad (16)$$

The insurance company's net benefit from the incentive program is given as

$$Q_{IC} = \Delta K - \Delta V = K_0 = \sum_{i=1}^{N} \sum_{j=1}^{J_i} \sum_{r=1}^{m_j} \lambda \left(\kappa - k_r \right) \left(p_{ijr}^{(0)} - p_{ijr} \right) - \sum_{i=1}^{N} \rho_i \gamma_i. \quad (17)$$

5.5.4 *Optimization of the Incentive Program*

Optimization of the incentive program can be formulated as a bi-level problem. Both the insurance company and the logistic company try to maximize their benefit, the former by means of settings in the variable premium scheme and the latter by means of settings in the incentive structure. The bi-level programming problem can be expressed as

$$\text{upper level: } \max_{\rho_i} Q_{IC}; \quad (18)$$

$$\text{lower level: } \max_{b_{ij}} Q_{LC}. \quad (19)$$

On both levels we see a trade-off between two cancelling measures. For the logistic company, if the incentives are high in value then drivers' compliance level will expectedly be high and as a result the premium rates will be lowered substantially. This way the logistic company pays more to the drivers and less to the insurance company. If incentives are lowered, the logistic company pays less to the drivers but more to the insurance company.

For the insurance company, if very competitive premium rates are offered for high compliance vehicles (i.e. with high ρ_i), then we expect the incentives, the compliance ratio, and subsequently the safety to be high. This means that the accident pay-out will be low. This way the insurance company receives less revenue while paying out less accident costs. If the rates are not so competitive (i.e. with low ρ_i), revenue will be higher but so is the expected accident pay-out due to low compliance of safety instructions.

The same trade-off also applies to the individual drivers. If they do not comply with the safety instructions they will not receive any bonus but may well save travel time or fuel cost. Even though the drivers have no direct control of the variable premium scheme or the incentive structure, they indirectly influence them through their route choice behaviour.

A win-win situation is said to exist when

$$Q_{LC} \geq 0, Q_{IC} \geq 0. \quad (20)$$

Equivalently, this means

$$K_0 - K \geq V_0 - V \geq B. \quad (21)$$

The inequalities in (21) are actually the necessary and sufficient conditions for a win-win situation. Based on the bi-level formulation in (18) and (19), we expect that the optimization of the incentive program will reduce the logistic company's benefit to almost close to zero. This is because the insurance company, being at the upper level of the optimization, will choose the premium discount rate ρ_i in such a way that the difference between $K_0 - K$ and $V_0 - V$ (i.e. its own benefit) is maximized. By doing so, the difference between $V_0 - V$ and B (i.e. the logistic company's benefit) is minimized. In practice, we expect the insurance company to choose ρ_i so that a reasonable benefit is also assured for the logistic company, in order to persuade the latter to participate in the incentive program.

5.6 The Results and Implications from an Online Survey

We developed an online Route Choice Survey (RCS) to study drivers' response to the incentive structure. The survey was located on a web-server (available at http://www.routekeuze.eu). The target group was Dutch professional drivers and for this reason the interface was prepared in the Dutch language. In the beginning of the survey some background information was given to the respondent, explaining the incentive structure and describing the choice situation. In the main part of the survey, 20 choice questions were presented to the respondent. These include 10 "before" questions (i.e. without the incentives; Figure 5), followed by 10 "after" questions (i.e. with the incentives; Figure 6).

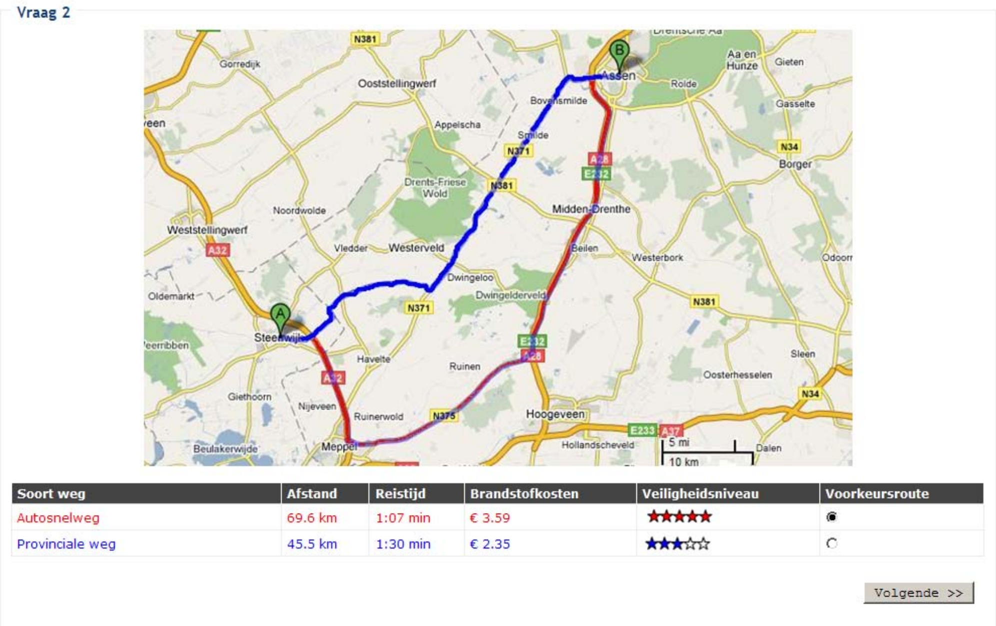


Figure 5 Screenshot of a before question (without the incentives).

Each choice question consists of a question map and an answer module. The question map displays the route choice situation. Origin and destination are presented by A and B, respectively. Two options are highlighted on the map: the safest route (red colour) and the alternative route (blue colour). The answer module presents the properties of two options, including road type, route distance, travel time, fuel cost and safety scores (represented by 1~5 filled stars). For the after questions the module further includes a column of the amount of incentives (*beloning*). Respondents make their route choices by clicking on the radio buttons right next to the options in the answer module. After a selection is made the ‘Next’ (*Volgende*) button will be activated and the respondent may proceed to the next question.

In total, 20 choice situations (i.e. with 20 different maps) are used. These include road networks from the Netherlands (NL), from Europe but outside the Netherlands (EU) and from the United States (US). For each respondent, a random sample of 10 choice situations are presented as before questions (i.e. without the incentives displayed; see Figure 5) and the rest 10 choice situations are presented as after questions (Figure 6). In this way each respondent will face 20 different choice maps while the same choice map has an equal opportunity to be presented as a before question or as an after question. When a large number of respondents have participated in the survey, a choice map will expectedly have equal numbers of before answers and after answers.

Figure 6 Screenshot of an after question (with the incentives).

5.6.1 *The Preliminary Results*

The online survey was conducted between June 4 and June 24, 2009. Respondents were attracted by contacting logistic and service companies; the web link of the survey was then distributed via their internal email systems. In the end, a total of 45 professional drivers answered the survey. Not every one of them completed the 20 questions in whole, resulting in 438 answers for before questions and 356 answers for after questions. Of the 794 answers in total, 283 were made on NL maps, 355 on EU maps, and 156 on US maps.

Table 3 shows the distribution of the choice answers. A clear difference is observed in the probability of the safest route being chosen against its alternative without or with the incentive structure: an average of 50% for the before questions, compared to 58% for the after questions. A t-test on the 20 pairs of percentages reveals that the after percentages are significantly greater than the before percentages (at significance level $\alpha = 0.05$; t value = 2.31, critical t value = 1.73). Despite the significant difference, we notice nonetheless that 5 out of the 20 choice maps observed a decrease rather than increase in the percentage of choosing the safest route. This observation is beyond our explanation. However, we note that these 5 cases happened only to European road networks (the two non-Dutch ones being in Italy and Switzerland, respectively), which the respondents are more familiar with than American road networks.

Table 3 Route Choice Survey: Choice Counts Before and After.

Map	Location	Before questions			After questions			Change in % choosing safest route
		# choosing safest route	# choosing alternative route	% choosing safest route	# choosing safest route	# choosing alternative route	% choosing safest route	
1	EU	21	2	91.3	15	0	100.0	8.7
2	EU	21	5	80.8	14	1	93.3	12.6
3	EU	6	10	37.5	14	12	53.8	16.3
4	EU	18	6	75.0	9	9	50.0	-25.0
5	EU	15	9	62.5	9	8	52.9	-9.6
6	US	3	18	14.3	7	13	35.0	20.7
7	US	14	9	60.9	11	7	61.1	0.2
8	US	3	19	13.6	9	5	64.3	50.6
9	US	18	7	72.0	11	2	84.6	12.6
10	US	7	14	33.3	6	9	40.0	6.7
11	NL	7	15	31.8	5	13	27.8	-4.0
12	NL	6	13	31.6	19	1	95.0	63.4
13	NL	12	12	50.0	9	7	56.3	6.3
14	NL	18	7	72.0	11	7	61.1	-10.9
15	NL	7	14	33.3	11	9	55.0	21.7
16	NL	9	12	42.9	5	12	29.4	-13.4
17	NL	13	9	59.1	12	8	60.0	0.9
18	EU	7	11	38.9	13	6	68.4	29.5
19	EU	6	16	27.3	7	11	38.9	11.6
20	EU	8	11	42.1	11	8	57.9	15.8
Total		219	219	50.0	208	148	58.4	8.4

5.6.2 *Estimation of the Route Choice Model*

Although the results in Table 2 give some indication on drivers' behaviour shift, they do not take into account the differences between the individual choice situations. The gap between the two options in terms of travel time, fuel cost, and the amount of the incentive, will certainly affect drivers' preference towards/against the safest route. Therefore, the survey data were also used to estimate the logit choice model.

Table 4 shows the regression results of the logit route choice model (8). Note here the units of the attributes used in the sample data: t_r (minute), c_r (Euro), k_r (safety star, 1~5), b_r (Euro). The dispersion parameter θ is fixed at 1. Insignificant parameters are marked with an asterisk. Overall the results for different sample groups are consistent with each other, taking into account the following facts: (a) the dispersion parameter is fixed at 1 for all groups; (b) travel time and fuel cost are correlated in the choice questions; (c) safety levels and the incentives are correlated in the choice questions.

The regression results are also consistent with the assumptions that travel time and fuel cost contributes negatively to the route utilities, while safety and reward contribute positively. These lead to negative β_1's and β_2's, and positive β_3's and β_4's in the regression results. The only exceptions are: β_3 for before only and after only, β_2 and

β_3 for US. In all four cases the parameter is insignificant, indicating that the sign of the parameter is less important because of its proximity to zero. Besides, the correlations discussed above may account for these irregularities.

The results show that drivers do take the reward into account, to an extent that reward is more important that fuel cost (compare the magnitude of β_2 and β_4). In contrast, drivers consider to a much lesser degree the safety level of a route (insignificant β_3). This implies that reward can be an effective way to encourage drivers to take the safest routes.

Table 4 Utility Parameters of Logit Route Choice Model: Regression Results.

	All	Before only	After only	NL	EU	US
Sample size	794	438	356	283	355	156
β_1	*-0.0425*	*-0.0556*	*-0.0446*	*-0.00540**	*-0.160*	*-0.129*
β_2	*-0.279*	*-0.0988**	*-0.881*	*-0.987*	*-0.310*	*0.143**
β_3	*0.0427**	*-0.180**	*-0.0556**	*0.598*	*0.171**	*-0.434**
β_4	*0.434*	0	*1.24*	*0.683*	*0.402*	*0.460*

*: insignificant.

5.6.3 *Cost-Benefit Analysis for the Logistic Company and the Insurance Company*

The cost-benefit balances for the logistic company and the insurance company apparently depend on the road network and the types of trips made. As an indicative numerical test, we consider the trip situation illustrated in Figure 5 and apply the route choice model with the parameters as the regression results for all samples in Table 4. Before the incentive program is implemented, choice probabilities for the safest route and the alternative route are 0.672 and 0.328, respectively. The expected safety level as expressed in 1~5 stars is then 5*0.672+3*0.328 = 4.34.

With the incentive program were €1 is awarded for following the safest route, the choice probabilities become 0.760 and 0.240. And the expected safety level is now 5*0.760+3*0.240 = 4.52. So by expectedly paying B = 0.760*€1 = €0.76, the logistic company raises the safety level by 0.18 star. If the resulting reduction in expected accident cost is greater than €0.76, say ΔK=€1, then the variable insurance premium can offer a discount of ΔV=€0.80. By doing so the insurance company has a net benefit of €0.20 for this trip, while the logistic company receives a benefit of €0.04. A win-win situation is then established.

5.7 Discussion and conclusions

This project introduced an innovative approach for traffic safety enhancement, namely a route-based incentive program operated by a logistic company together with an insurance company. A win-win situation for the two companies was demonstrated to exist dependent on driver behaviour, the road network, as well as the settings in the incentive program. The next step of our research is to further develop the theoretical framework and to conduct a more comprehensive cost benefit analysis for the stakeholders.

The online survey used in this study is a stated preference technique to investigate driver behaviour in future situations. In order to draw solid conclusions we intend to attract more respondents than the current amount of 45. On the other hand, when the incentive program is put into practice, the actual driver behaviour (i.e. revealed preference) may differ.

The impact of several assumptions in this study needs to be addressed in follow up studies. In particular, the benefit of the logistic company depends on not only the safety aspects but also other factors such as cost and operation efficiency. If drivers take longer route because of the incentive program, higher fuel cost is expected which is in the end carried by the logistic company. Due to longer travel time per journey, the number of deliveries that a vehicle can do per day might also be reduced. A more comprehensive cost benefit analysis is therefore necessary from the logistic company's point of view.

Adopting the incentive program on a societal level is also a point of interest for future studies. Similar (but contrary) to road pricing, drivers pay for the marginal cost they incur on society and get rewarded for the marginal benefit they bring to society (by taking safer routes). For this implementation, social acceptance and financial viability must be assessed beforehand.

It is also important to realize the complexity of the traffic system; many settings may be "tuned" in an effort to optimize the incentive program. The two most essential factors would be location (e.g. highway, or around city centre) and timing (e.g. dynamic, peak hour only). If training effects on the drivers are expected, the incentive program can be planned to be temporary, while achieving a long term effect nevertheless. Another issue is the "shockwave" in network flow right after the program is implemented (Bie, van Arem, and Lo, 2008). This can be modelled as a dynamical system problem.

6 Field Operational Test

This chapter describes the Transumo IV Field Operational Test (FOT) or professional pilot, were professional drivers were driving in a real-traffic environment. During the test that lasted 2 months, the driving behaviour and route-choice of professional drivers were measured. The vehicles were equipped with a navigation system, which could generate a fastest and a safest route to a given destination (see Chapter 4 for the safest route algorithm). After one month, the participants were rewarded if they drove the safest route (see Chapters 3 and 5 for the incentive framework).

6.1 Project organization

The professional pilot was organized by a consortium consisting of several knowledge institutes (SWOV, TNO, TU Delft, and University of Twente) and a privately owned company (STOK Nederland BV).

STOK was project leader of the pilot, performed the practical organization, the execution, and organisational and communicational issues with the external participants (insurer, haulier/entrepreneur, participants). Furthermore, STOK was the supplier of the logging-systems, back-office and the feedback website. The definition of the safest route algorithm was performed by SWOV (Chapter 4) and TNO. In addition, TNO assisted in the project management of the pilot (i.e. helping to keep to the time schedule), the development of the incentive structure, the definition of the experimental design and the behavioural analysis.

Other involved parties where:
- The insurance company Univé.
- The transportation company Energie Service Noordwest (NUON affiliation). In total 30 drivers (service mechanics) from 4 different locations were recruited for the pilot.
- The navigation system and software supplier STOK and Geo Solutions.
- The company Falkplan-Andes, who provided the digital mapping and implemented the safest route algorithm.

6.2 Method

6.2.1 *Set-up of the Professional Pilot*

The objective of the Professional Pilot was to collect data on the behaviour of end-users (in their working environment) being offered an alternative safe route navigation routine next to the ‘normal’ fast navigation routine. In order to persuade the end-user to choose a safer route the driver was offered a financial incentive for choosing the safest route. Their employer’s insurance company paid this incentive.

To this end, an in-car interactive navigation platform had to be created that offered the driver the opportunity to choose a safest route instead of a fastest route. In this process, the following steps were executed:
- Implementation of a safest route algorithm.
- Development of navigation software that handled the safest route algorithm.

- Acquirement & development of PNDs (personal navigation devices) that handled the navigation software.
- Enabling that STOK's OBUs (On Board Unit) communicated with the in-car PND.
- Development and implementation of an interactive ICT platform to monitor the driving behaviour and enabling the back-office to communicate directly with the individual end-users via the PND and a dedicated website.
- Recruitment of a group of professional test-drivers.
- Getting an insurance company involved.

6.2.2 *Conditions*

In the pilot study, a baseline condition and two navigation conditions were driven, as explained in the subsections below.

6.2.2.1 *Baseline condition: no navigation system*

In the baseline condition, the participants drove and navigated as they did normally. The participants did not have a factory-fixed navigation system in their car and they assured that they would not use a mobile navigation device during the experiment.

6.2.2.2 *Phase A: navigation system without an incentive*

In condition *A,* the participants drove with the STOK navigation system (details of this system are described hereafter). The participants had the choice to use or not use the navigation system. They drove without an incentive structure, i.e., they did not get a reward when the safest route was selected and driven. In the case they decided to use the system, two different route choices were possible: the traditional fastest route and the alternative safest route. The selection could be made by touching the screen. It was recommended that for both route options the time of travel and distance of travel was indicated (see Figure 7).

	Travel time	Length
Fastest route	32 min.	40 km
Safest route	38 min	42 km

Figure 7 Example of selection display.

In the pilot only the choice of fastest or safest route could be made. The indication of the expected travel time and length was not implemented. After selection of one of the route options, the driver was directed either to the fastest or to the safest navigation system menu. In this menu, the destination had to be entered and the travel time and length became visible.

The fastest route was calculated on the navigation system itself. The route was calculated after the destination was entered. The system calculated a new route during trip in case the participant did not cohere with the route that was advised. A 2D map provided the information visually.

The calculation ability of the used navigation system was insufficient for calculating the safest route. Therefore, the safest route was calculated at a back-office. In the safest route menu, the destination had to be entered. Next, this destination data was sent wireless via the in-vehicle on-board-unit (OBU) to a back-office. The back-office is a central computer were the routes were calculated. After calculation of the route, the waypoints were sent back to the in-car navigation device.

Because of the calculation in the back-office, the performance of the safest route system was different compared to the fastest route system. The time duration between sending the origin-destination information and receiving the way-point information took initially 30s to 6min, this was later on adjusted to approximately 1 min. This information exchange was a function of the car velocity (the sample rate was based on displacement instead of time based, i.e. every x meters a message was sent). The communication went faster when the car was driving faster. Initially, when the vehicle was parked or was driving at an unknown road (for the digital map), an error occurred in the device and the device had to be restarted. No new route was calculated when a participant drove another route than the suggested route. Initially as well, a route could be advised in which the participant had to drive an unnecessary longer route. This was improved by changing the settings during the base-line driving.

6.2.2.3 *Phase B: navigation system with an incentive*

Phase B equals phase A, added with an incentive when participants drove the safest route. The financial incentive was provided afterwards to the participants, but the fact that a financial reward would be provided for following the safest route, was communicated to the participants beforehand.

The behavioural data of the baseline condition (no navigation system) was not used in the analysis described in this report. The reason was that due to technical problems, no data were made available to distinguish between the different navigation means: fastest route, safest route and no-navigation.

6.2.3 *Incentive structure*

An incentive was provided to motivate the participants to drive the safest route instead of the fastest route.

The company Univé provided to STOK a fixed part of the total required financial incentive. The available amount of money for the whole trial was fixed at 5,000 Euro.

At the time instant the safest route was advised (by the navigation system), one could not determine how high the, e.g. weekly paid, reward would be, since the reward depended on future information. The budget available for the incentives was fixed, but the distribution among the participants depended on the route choice behaviour, for example, how often in a week time all the participants chose the safest route.
To prevent under or overspending, a similar approach as the Belonitor project (Griffioen & Hoedemaeker, 2004) was recommended; TNO developed an incentive structure using ‘stars’.
A participant was rewarded with a ‘star’, for every safest route that was chosen and driven (for ~95% of the generated route). A larger number of stars indicated a high incentive, were the absolute incentive did not exactly match with the number of stars, i.e., there was no fixed amount for each star.

The incentive could be determined in 2 steps:

(1) Determining safety incentive score
The proposal for the incentive structure was based on the number of times the safest route was driven. The aim was to follow the safest route, even if this route equals the

fastest route. The participant earned a star by driving the safest route. After completion and coherence with the advised route, the navigation notified the driver directly of the earned star. This direct notification of a reward is an important aspect to achieve a behavioural change (Griffioen & Hoedemaeker, 2004). The route was to be considered fully followed by the system when:

- the driver did not deviate from the advised route,
- the distance to the destination was within a radius of 500m.

However, during the pilot the process was carried out in a different way. The company STOK determined the number of safest routes driven and sent the earned stars in a text message once-per-day to the participants. The algorithm that STOK used to determine whether a safest route was driven is unknown. Participants with no earned stars did not receive a text message.

Besides directly indicating that a safest route was fully driven, it was recommended, that the following information was displayed in a continuous way on the navigation device's display:

- total number of stars earned that day,
- the total number of stars earned during the entire test.

To achieve a behavioural change it is important that the driver has the ability to compare his current behaviour with his previous behaviour.

The described feedback of information was not implemented in the personal navigation device.

(2) Determination of the incentive (once per month, post-processing)
The proposal how the incentive for each participant was determined, is explained next. Each participant had at the end of each month a score *s*. This score was determined by number of days d_{month} the participant worked that month and the ratio between the earned starts n_{stars} and the total number of routes he has driven that month n_{all}. The total number of routes n_{all} is the sum of the routes driven without a navigation system, with a navigation system and the fastest route, and with a navigation system using the safest route.

$$s_p = \frac{n_{stars,p}}{d_{month,p}\, n_{all}}$$

Subsequently, the incentive *r* was calculated for each participant *p*. The payment for participant *p* per month depended on the fixed budget per month (2,500 Eur) and the ratio between the score of a participant, s_p, and the sum of the scores of all participants $\sum_{i=1}^{30} s_i$.

$$r_p = \frac{s_p}{\sum_{i=1}^{30} s_i} 2500$$

However, STOK used another approach to determine the incentive. The total number of possible routes per day per test-driver according to the work planning was 12 to 20 based on 6 to 10 jobs per day. At a maximum, this would result in 20 routes per day per test-driver. These 20 routes multiplied by 5 working days results in a maximum of 100 routes per week. The fixed available total incentive per week divided by 300 (30 x 100) was used as the financial incentive per safest route. Hence, the incentive for a 'star' was fixed. Furthermore, a variation in the number of working days and the possible number of routes was not included.

The rewards were paid monthly as addition to the salary.

6.2.4 *Route algorithm*

The algorithm to determine the fastest route was a conventional algorithm, which is used typically to determine the route in a fastest way for mobile navigation systems. The basis for the safest route algorithm was a theoretical model developed by the SWOV (see Chapter 4). This model contains specific safety requirements and provides the basic building blocks for the safest route routine. The practical definition of a route was determined in a number of steps. Firstly, a top 10 of fastest routes was determined. Next, a safety score was calculated for each route, as explained in Section 4.1.
This safety score was based on the nine-criteria of the SWOV. The weighting factors for the nine criteria were initially set equal. The route with the best safety score was defined as the safest route. Together with STOK, Falkplan-Andes BV (Falk) implemented the safest route algorithm.

Geo Solution in cooperation with a French company and STOK developed the required navigation software to handle the safest navigation routine. This safe-route algorithm was too complicated to integrate into a stand-alone PND (Personal Navigation Device) itself. Therefore Falk implemented the algorithm that was specified by STOK and Geo Solution. This algorithm run at the STOK web application. A route request from the PND was send to the web application, was processed and the results (the safest route) was sent back to the PND.

During the pilot (Phase A), an upper bound to the route length was set. More precise, the maximum allowed detour length was changed. Initially the safest route was often too long, such that the participants would almost never choose it. The maximum detour length was set from 30% to 20% with regard to the length of the fastest route.
In addition, some bugs in the routing algorithm of Falk were fixed, for example on- and off ramps were used too often in the advised routes in the first version of the algorithm.

6.2.5 *Apparatus*

6.2.5.1 *In car navigation – The personal navigation devices (PND)*

During the project, a navigation device with an open API (Application Programming Interface) was used. An open API enables programmers to add new features to the software of the navigation device or modify certain routines. The popular PNDs currently in the market are for about 99% <u>without</u> an open API. This means that no third party can access and modify the firm- and software. The reason is probably twofold. Firstly, the navigation companies are eager to keep control of their own devices. Secondly, the companies are looking towards creating their own services. As a consequence, for the targeted application in this project, we were forced to look for smaller companies that develop and/or produce their own navigation device. There are a many of these companies but the quality of hardware was often not sufficient or the provided services were not reliable. After a challenging search, an Asian company was found that could provide a PND with an open API.

Each of the vehicles (vans) was equipped with such a PND (see Figure 8).
The navigation system had a CPU to calculate the fastest route. It used a separate GPS device to determine the current locations. The device was connected to a back-office via the STOK OBU (On Board Unit).

The use of a connected navigation device with remote route calculation results in extra costs compared to onboard calculation. Over the air data communication requires a SIM-card.

The moment data can be compressed to an acceptable size, the communication speed over the air can be compared to onboard calculation time and the dataflow can be individually monitored and controlled in real time, connected navigation is preferable over onboard navigation. With connected navigation, applications and On Demand Services can be easily added. Back-office information systems can be interconnected in real time which gives end-users access to valuable information sources.

Figure 8 Personal Navigation Device.

6.2.5.2 *STOK On Board Unit (OBU)*

The STOK OBU took care of the data acquisition and the data transmission (GRPS) to and from the back-office. See Figure 9. The box handles:

- Lateral and longitudinal accelerations (internal accelerometer).
- GPS position (external GPS device).
- Velocity (derived from the GPS position).
- Communication with the navigation system and the remote back-office server.

Figure 9 STOK on board unit.

6.2.5.3 *Integration*

A web-interface was developed between the STOK back-office and the server at Falk. STOK's technicians created an interface between the PND and the STOK OBU (On Board Unit) to avoid having to install two individual SIM-cards used for the communication interface with the back-office applications. The OBU acts as middleware. Using the OBU, STOK potentially could monitor every test vehicle and communicate with the end-user directly by using the navigation screen.

In combination with interactive communication, these real-time location based services (LBS) can be time- and cost saving but also entertaining and very helpful to end users. The possibility to access real time information that is of interest to you at a certain moment in time could be addictive and in time people will surely depend on it. Location based value added services can open up new (niche) markets at low costs and at the same time be used for changing behaviour and contributing to sustainable mobility.

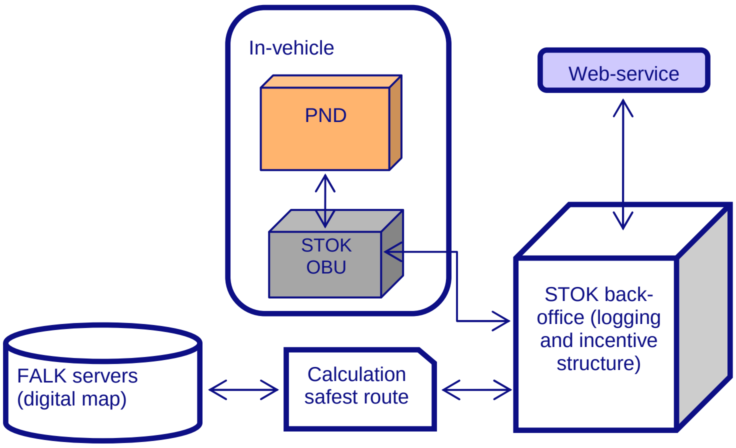


Figure 10 Integration of the components.

6.2.6 *Participants*

The company Univé helped STOK to recruit a test-fleet. The participants for the professional pilot were employees of the Energy Service Noord West, a NUON affiliated Energy Service Company. Participants were selected from the total group of employees. The selection criteria of STOK were based on the assumption that the group had to be as diverse as possible with respect to age and number of active working years. They drove delivery vans, type Renault Kangoo. Initially, the total fleet size was 31. However, during the pilot three drivers were fired and their vans were sold.

Furthermore, 3 black boxes appeared to be broken and the cables of one unit were broken down. Finally, the driver of one van was changed. This brings the resulting fleet size to 23 vans.

6.2.7 *Procedure*

STOK briefed the participants of the professional pilot. The participants were specifically informed that they individually could earn a financial incentive by choosing a safest route. In the first week of the study, the participants became acquainted with the installed PND. Next, a period of four weeks started were the driving behaviour was monitored without rewarding any incentive. Subsequently, a period of four weeks started were the participants were rewarded. Table 5 summarizes the resulting timeline of the study.

Initially the incentive-phase would have been six weeks but due to software problems on the PND the incentive-phase stopped after four weeks.

Table 5 Timeline of the conditions.

Phase	Navigation	Duration (week)	Incentive
Baseline	No	1	No
A	Yes	4	No
B	Yes	4	Yes

6.2.8 *Data registrations and analysis*

In the pilot-preparing phase, both objective and subjective data would be collected. The subjective data consisted of questionnaires that would be handed out to the participants. At three times subjective data would be gathered.

1 before the start of condition A,
2 before the start of condition B,
3 after condition B.

STOK has handed-out the first and second questionnaire twice. However, only some drivers have filled out the questionnaire. TNO did not receive these data for analysis.

As mentioned, the objective data included:

– Lateral and longitudinal accelerations (internal accelerometer),
– GPS position (external GPS device),
– Velocity (derived from the GPS position).

Furthermore, due to technical and procedural reasons, it was <u>not</u> possible to store the following signals:

– the status of the PND, the safest route, fastest route, no navigation,
– entered destination,
– driven road type, e.g.: motorway,
– current speed limit.

The data were analyzed by means of student t-tests and cumulative distributions are compared by using the non-parametric Kolmogorov-Smirnov test.

6.3 Results of the professional pilot

This section describes the results of the professional pilot. Two conditions were compared. In condition A the participants drove 4 weeks without an incentive and had the possibility to use a navigation system with both the fastest and the safest route option. Condition B is similar to condition A, with the distinction that the participant could earn a financial incentive when he drove the safest route.

6.3.1 Differences between safest and fastest routes

A first question is whether the generated safest routes differ from the fastest routes. To give an indicative answer to this question, 1221 fastest and safest routes (with the same origin and destination) were off-line generated and analyzed. The origins and destinations were taken from 20 participants of the F.O.T. in the period from June 9 to June 23 2009. For both route options, the travelled distances for each of the three road categories (access roads, distributor roads, and through roads, see also Chapter 4) and the total travelled distance were calculated.

It was found that in 78 % of the cases, the safest route and the fastest route were equal and that 22% of the routes were different. This equality is an important requirement for the sustainable safety principle (see also Chapter 4). Figure 11 shows the cumulative distribution for the travelled distances for the 22% of routes that were different. A statistical non-parametric Kolmogorov-Smirnov test showed that the distributions between the fastest and safest route were different ($p<0.0001$). The figure shows that the total travelled distance (distance total) for the major part of the routes is larger for the safest routes compared to the fastest route. More detailed: for the safest route, more distance is travelled on access and through roads. In contrast, less distance is travelled on distributor roads.

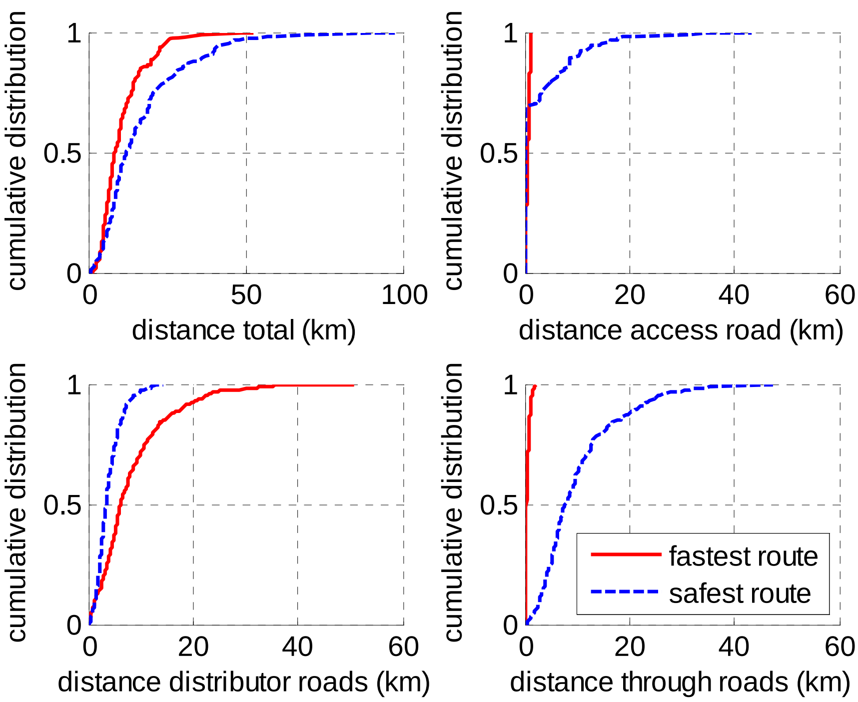


Figure 11 Cumulative distribution of the travelled distances for the different fastest and safest routes.

Section 4.2.2 describes key safety indicators to quantify the safety of routes. Here we use a different approach to compare the safety of both routes. By multiplying the distance travelled on each road type and the average injury figure for that road type (Table 6), an indication of the safety of each route can be calculated. Figure 12 shows the cumulative safety scores for the different safest and fastest routes. It shows that for this selection of routes and for this particular safety indicator, the safety is better for the major part of the safest routes compared to the fastest routes (a Kolmogorov-Smirnov test showed that the distributions between the fastest and safest route were different ($p<0.0001$)).

Table 6 Injury figure per road type.

Road type	Injury figure (number of injuries per million kilometres)
Through	0.07
Distributor	0.54
Access	0.57

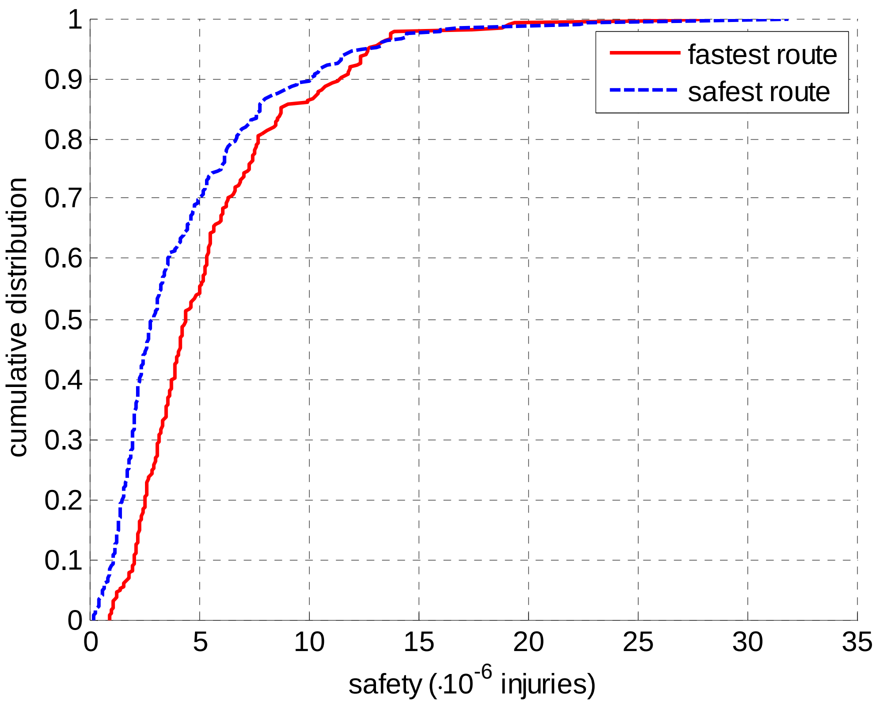


Figure 12 The cumulative distribution of the estimated injury figure for the selected routes.

6.3.2 *Differences between participants for safest and all trips*

In order to explore the differences between participants, the data of 12 of the 23 remaining professional drivers in the period from April 27 to June 20 2009 were used. For the excluded participants, parts of the data were either missing or not valid: the velocity data of two participants was missing and two other participants drove never a safest route in the observed period. Figure 13 shows the number of safest routes that each of the twelve participants drove. The number of safest routes was determined by STOK. Participants *IV04*, *IV21* and *IV25* drove together 80% of all safest routes. Each star was worth a fixed amount of 2.78 Euro.

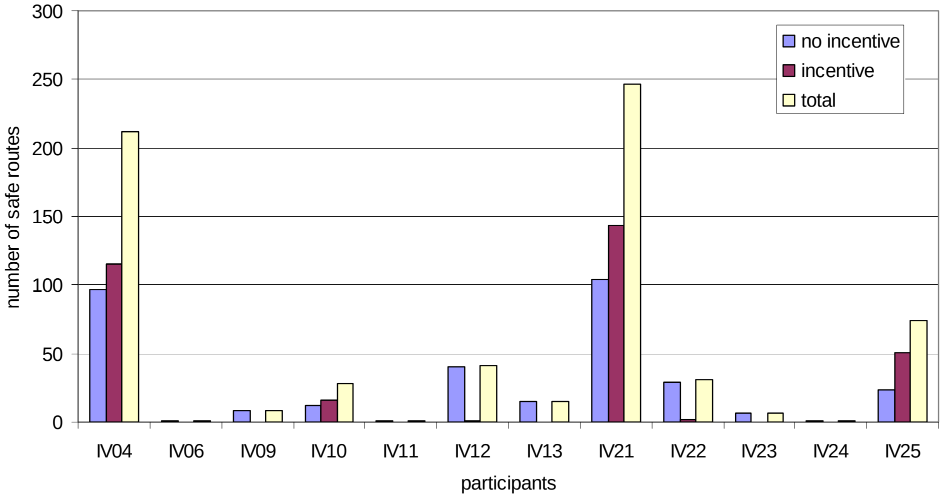


Figure 13 The number of safest routes each participant has driven during the no-incentive period, the incentive period and the total number safest routes during the total period.

The total number of trips each participant made is shown in Figure 14. The number of trips was derived from the behavioural data that were logged. A trip was defined as a route with a minimum duration of 5 minutes. When a participant had a zero velocity for less than 1 minute, this was still accounted for the same trip. Note that the definition of a trip differs between Figure 13 and Figure 14. In Figure 13 the number of trips was determined by STOK. In Figure 14 the number was calculated based on the logged velocity data.

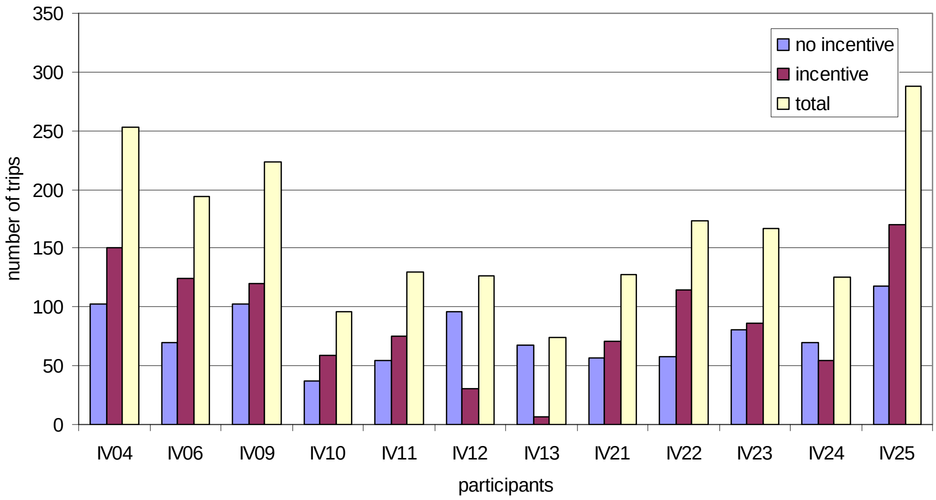


Figure 14 The number of routes each participant has driven during the eight weeks.

By combining Figure 13 and Figure 14, one can determine the ratio between the number of safest routes and the total number of trips (Figure 15). It shows that participant *IV21* drove more safe trips than the total number of trips. This effect is explained by the difference in the definition of a trip. This participant (and other participants) drove probably trips (and entered a destination) with durations smaller than 5 minutes.

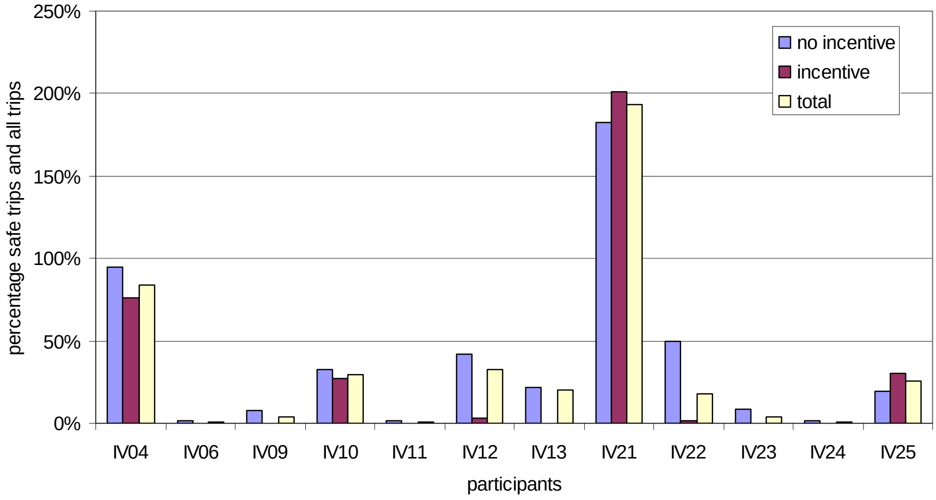


Figure 15 The ratio (in percentages) between the number of safest routes and the total number of trips.

Figure 15 shows that many participants used the safest route option a bit more often in the no-incentive period compared to the incentive period. This initial use of the safest route can be seen in Figure 16 as well. This figure shows the mean percentage of safest routes on the vertical axis. The horizontal axis shows the days of the week. The squares indicate the percentage of safest routes for that day. The diamonds indicate the percentage of safest routes per week. The smooth solid line indicates the moving average percentage of safest routes. The window length of the moving-average filter is one week. It seems that during the first days of condition A, the participants used safest route more often than the last days (end of week 4). In condition B, which starts at week 5 and ends at week 8, the percentage seem more or less homogenous. The outliers are caused by participant *IV21*.

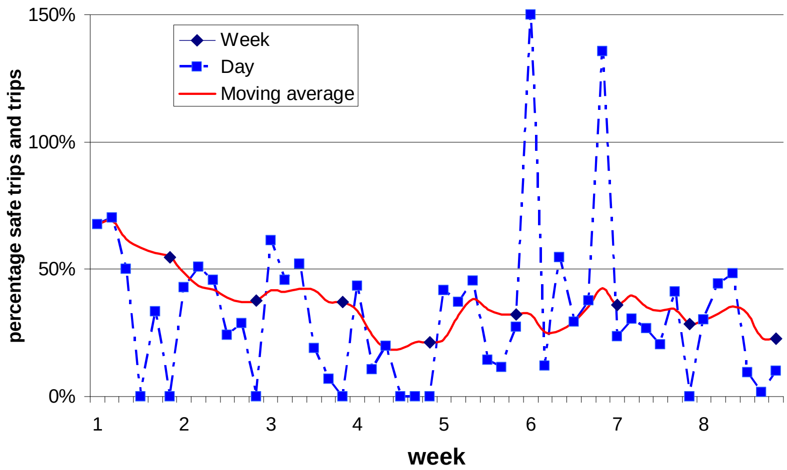


Figure 16 The mean percentage of the driven safest route compared to all trips.

6.3.3 *Effect of incentive*

Figure 17 shows the ratio between the number of safest trips and the total number of trips for two conditions; with an incentive and without an incentive. No effects were found between the two conditions (p=0.086). This means that in this study the financial incentive had no effect on the route choice of the participants. Moreover, the initial use of the safest route option had no influence on the results as well, i.e., also no effect was found by excluding the first two weeks from the analysis.

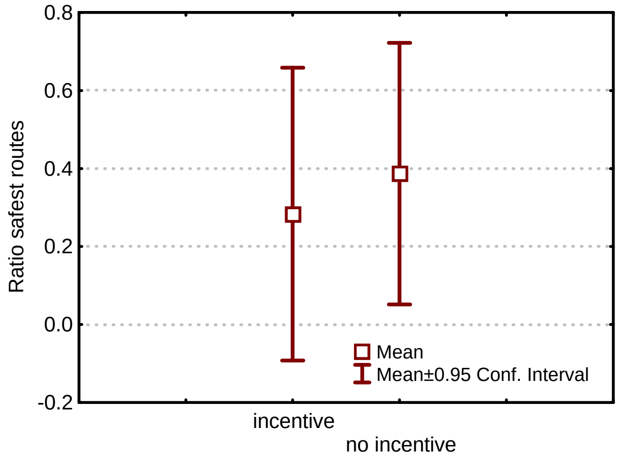


Figure 17 The ratio between the number of safest trips and the total number of trips for two conditions.

6.4 Discussion and conclusions

The used route algorithms have been compared for a sample of origin-destination points taken from the field operational test. In the comparison between the resulting safest and fastest route, it was found that in 78% of the cases the trips were equal. This result is an important requirement for the sustainable safety principle were one is aiming at both safest routes and fastest routes. For the remaining 22% of the cases, there were differences between the fastest and safest routes. The travelled distance for the safest route was predominately longer compared to the fastest route. The differences were caused by an increase of travelled distance on through roads and access roads. Note that the comparison between the route algorithms was based on the already adapted algorithms. That is, during the pilot the maximum allowed detour length for the safest route was changed.

The FOT did not show a positive effect on the use of an incentive as was hypothesized. There are many possible causes that could have had an influence on this result.
The main point was that both systems differed with respect to functionality and usability. The fastest route algorithm was implemented on the PND whereas the safest route was implemented at a back-office. This had many consequences, such as the required time before the system was ready for use. Therefore, the study did not explore the effect of an incentive on the route choice but rather on the technology used. Secondly, due to various technological set-backs the measuring period of the pilot was reduced multiple times. This affects the effect size. The variance in the outcome increases when the test time and number of participants decreases, with as result that a possible effect is not identified due to this increased variance. Thirdly, initially the route advice was unrealistic for the safest route option in the without incentive condition. This could have as effect that participants did not use this route-option again due to the bad experience, even with an incentive. Finally, the driver was not directly rewarded when a safest route was driven. They received there incentive once a month as an addition on their salary. From literature, we know that directly rewarding a participant has the best effect to influence ones behaviour. Concluding, a follow-up pilot is required to prove the effect of incentives to influence the route choice.

7 Survey on deployment options to influence user adoption

This chapter describes deployment aspects that were studied within the project Transumo IV. In contains a summary of the results with respect to the deployment of safest route navigation. The text in this chapter was contributed by the TU Delft.

7.1 ADAS deployment decision interactions

In the ‘Implementation Aspects’ subproject of Intelligent Vehicles, the focus was on deployment decision-making with respect to Advanced Driver Assistance Systems (ADAS). A conceptual model of the interactions between actor decisions was used as the basis for a survey on the probability that actors are going to apply deployment options to influence the user to buy an ADAS, and the probability that a user will choose to buy an ADAS (see Figure 18).

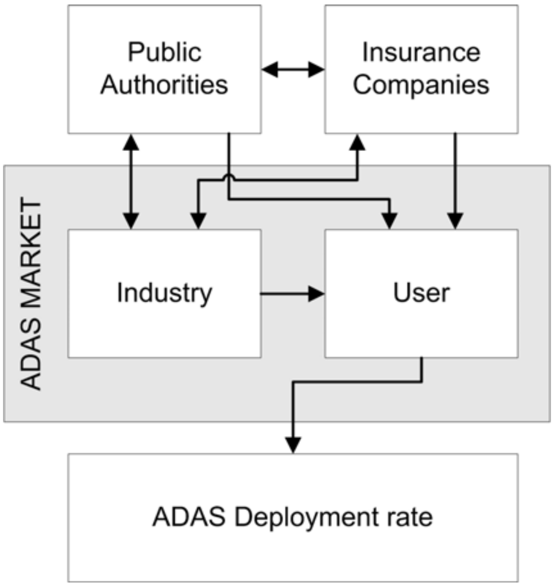


Figure 18 Conceptual model of ADAS deployment decision interactions.

Among all actors involved in ADAS deployment, public authorities, automotive industry, and insurance companies are considered as the actors who can most directly influence user adoption ADAS. These actors are all assumed to have a certain interest in the deployment rate of ADAS, as this may influence their objectives with respect to, for example, traffic safety or return on investment. And since they are all able to influence the deployment rate by influencing user adoption, it is expected that their decisions to apply certain deployment options influence the decisions of the other actors to apply deployment options.

The main questions to be answered here are:

– What is the probability that an actor (public authorities, automotive industry, and/or insurance companies) takes a certain ADAS deployment decision given the decisions of other actors? and,
– What is the probability that a user adopts an ADAS, given the deployment decisions of the actors?

In order to answer these questions, an actor and a user survey were performed, based on stated preference methodology, to collect data based on which models of actor and user decision-making could be estimated.

7.2 ADAS and deployment options considered in the actor and user survey

In both surveys, three different ADAS were considered, for each of which it was expected that another actor would take the lead in deployment (see Figure 19).
For public authorities, an assisting type of Intelligent Speed Adaptation (see Carsten and Tate, 2005) was considered, called a Speed Assistant. For automotive industry, Adaptive Cruise Control combined with Stop&Go was considered, called a Congestion Assistant (see Van Driel and Van Arem, 2005). And, for insurance companies, as the actor stimulating deployment within the professional pilot, safest route navigation was considered in combination with speed warning and headway warning, including feedback to the driver on how safe his driving is. This was called a Safe Driving Assistant.

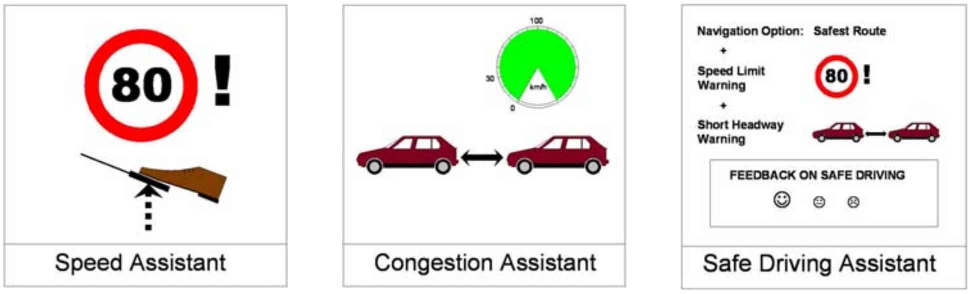


Figure 19 ADAS included in the deployment investigation.

In the actor survey, three deployment options were included for each actor, including doing nothing, a stimulation option (1,500 euro tax reduction for public authorities, ADAS as an option on new vehicles for automotive industry, and an optional insurance policy with up to 25% premium reduction for safe driving), and a forcing option (mandatory equipment with ADAS, ADAS standard on new vehicles, and a standard insurance policy with up to 25% premium reduction for safe driving respectively).

In the user survey, only the deployment options were considered in which the user still had a choice. Therefore, the starting point is that automotive industry provides the ADAS as an option. Tax reduction by public authorities was operationalized by varying the cost of the ADAS. Premium reductions by insurance companies were also varied.

7.3 Actor survey

The actor survey was set up to collect data on the probability that public authorities, automotive industry, and insurance companies will apply certain deployment options, given the deployment options already applied by the other actors.

7.3.1 Survey set-up

In the survey, respondents from public authorities, automotive industry and insurance companies were asked to indicate the probability that their sector would apply their three deployment options as defined above, given the ADAS to apply them to, and the deployment options the two other actors already applied to that ADAS. To the

deployment options, the option “other” was added, in order to set the required probability over all deployment options to 100%.
A total of 223 respondents were personally invited to complete the survey, and 75 reactions were received of which 72 were usable. This included 45 respondents from automotive industry, 20 from public authorities, and 7 from insurance companies.

7.3.2 *Model*

The following probability model, which is based on a general additive utility model, was estimated with the probability data resulting from the survey.

$$P(D_{1,a} = d \mid D_0 = x) = c + b_0 A + \sum_a b_a D_{0,a} + \varepsilon$$

$D_{1,a}$ = deployment option applied by actor a at time $t=1$
D_0 = decision scenario at time $t=0$
$D_{0,a}$ = deployment option applied by actor a at time $t=0$
A = ADAS
d = deployment option applied by decision-making actor
x = certain combination of deployment options of all actors
c = constant of probability model
b_0, b_a = coefficients of probability model

For each of the deployment options of an actor, a separate model was estimated, using multiple linear regression.

7.3.3 *Results: how to read the models*

The tables in the following sections present the probability models of all of the deployment options of one of the actors. The respective models are represented in the columns of the tables. The left side of the columns presents the coefficients of the models, which are explained in the first column, and the right side of the column presents the significance of the models. The first coefficient is the constant, which represents the average probability of applying the respective deployment option.
The remaining nine coefficients represent the three levels for each of the ADAS and deployment options of other actors included in the model. In case all attribute levels of an attribute were not significant across the models for an actor, they were not included in the tables. The last value in the left side of the column is the explained variance R^2. The value of R^2 should be interpreted as a relative measure (i.e. a model with a higher R^2 fits the data better), but not as an absolute measure, since its absolute value heavily depends on the experimental design.

The coefficients indicate the deviations from the constant and, therefore, the sum of the coefficients of the different levels for one attribute (i.e. ADAS or deployment option) is equal to zero. A negative sign of these coefficients means that in a situation including this attribute level it will negatively influence the overall probability. A positive sign positively influences the overall probability. The significance is only presented for the first and second attribute level, since these were included in the regression analysis. The third attribute level was calculated as the complement of the other two.

7.3.4 *Results: public authorities*

The public authority probability models (Table 7) show that the respondents expectations with respect to what public authorities will do are quite conservative. The average probability of doing nothing is relatively high, and that of mandatory deployment very low. The probabilities of doing nothing and tax reduction are influenced by industry offering ADAS as optional or standard equipment, but not to an extent that the rank order of the deployment options changes. The ADAS and the deployment options of insurance companies have no significant effect on the probabilities. The probability of other deployment options is comparable to that of mandatory equipment, but the explained variance is relatively low. The low probability and explained variance are due to the relatively small amount of respondents that used the possibility to choose for this option (4 out of 20 on average).

Table 7 Public authorities' overall probabilities to apply ADAS deployment options.

PUBLIC AUTHORITIES	**Do nothing**		**Tax reduction**		**Mandate**		**Other**	
Overall probabilities	coeff	*sig*	coeff	*sig*	coeff	*sig*	coeff	*sig*
Constant	62.333	*0.000*	20.000	*0.004*	8.161	*0.001*	9.506	*0.016*
ADAS								
Speed Assistant	-2.583	*0.277*	0.917	*0.652*	0.822	*0.146*	0.844	*0.671*
Congestion Assistant	-0.250	*0.899*	0.750	*0.709*	0.339	*0.440*	-0.839	*0.673*
Safe Driving Assistant	2.833		-1.667		-1.161		-0.006	
Industry action								
Do nothing	-4.750	*0.113*	3.417	*0.189*	1.172	*0.081*	0.161	*0.934*
Option	-7.833	*0.046*	5.833	*0.079*	0.339	*0.440*	1.661	*0.435*
Standard	12.583		-9.250		-1.511		-1.822	
Insurance action								
Do nothing	0.000	*1.000*	-0.333	*0.866*	-0.411	*0.366*	0.744	*0.707*
Option	-1.583	*0.460*	1.083	*0.598*	-0.344	*0.434*	0.844	*0.671*
Standard	1.583		-0.750		0.756		-1.589	
R Square	0.966		0.938		0.947		0.561	

By means of a cluster analysis, it was investigated if specific subgroups of public authority respondents with a clearly different opinion could be identified. No specific subgroups were found.

7.3.5 *Results: automotive industry*

The automotive industry probability models (Table 8) generally show that the probability that automotive industry will be taking action is relatively high, with the probability that they will offer ADAS as optional equipment being highest. The overall probability is mostly influenced by public authorities. Their influence is highest when applying mandatory deployment. The probability of other deployment options is very low, which is due to the small amount of respondents who used this option (5 out of 45 on average). The effects of the ADAS are generally not significant.

Table 8 Automotive industry's overall probabilities to apply ADAS deployment options.

AUTOMOTIVE INDUSTRY	Do nothing		Option		Standard		Other	
Overall probabilities	coeff	sig	coeff	sig	coeff	sig	coeff	sig
Constant	19.576	0.006	43.543	0.001	34.004	0.000	2.877	0.002
ADAS								
Speed Assistant	3.151	0.291	-2.600	0.263	-0.114	0.920	-0.433	0.126
Congestion Assistant	-1.096	0.670	1.233	0.541	-0.264	0.817	0.123	0.545
Safe Driving Assistant	-2.056		1.367		0.379		0.310	
Authorities' action								
Do nothing	13.668	0.025	5.010	0.097	-18.138	0.003	-0.543	0.086
Tax reduction	-2.092	0.444	10.680	0.024	-8.044	0.015	-0.543	0.086
Mandate	-11.576		-15.690		26.182		1.087	
Insurance action								
Do nothing	5.561	0.129	-3.197	0.198	-1.748	0.224	-0.617	0.069
Option	-2.872	0.324	1.347	0.508	0.996	0.426	0.530	0.090
Standard	-2.689		1.850		0.752		0.087	
R Square	0.963		0.980		0.997		0.969	

By means of a cluster analysis, it was investigated if specific subgroups of automotive industry respondents with a clearly different opinion could be identified. Three subgroups of automotive industry respondents were identified, and their characteristics are summarized in Figure 20. In this figure, the horizontal dashes mark the average probability of a deployment option (i.e. the constant), and the vertical lines mark the range of influence of (mainly) public authorities on the probability. The abbreviations of the deployment options on the horizontal axis should read as DN 1 = Do nothing, subgroup 1. The subgroup characteristic are discussed below.

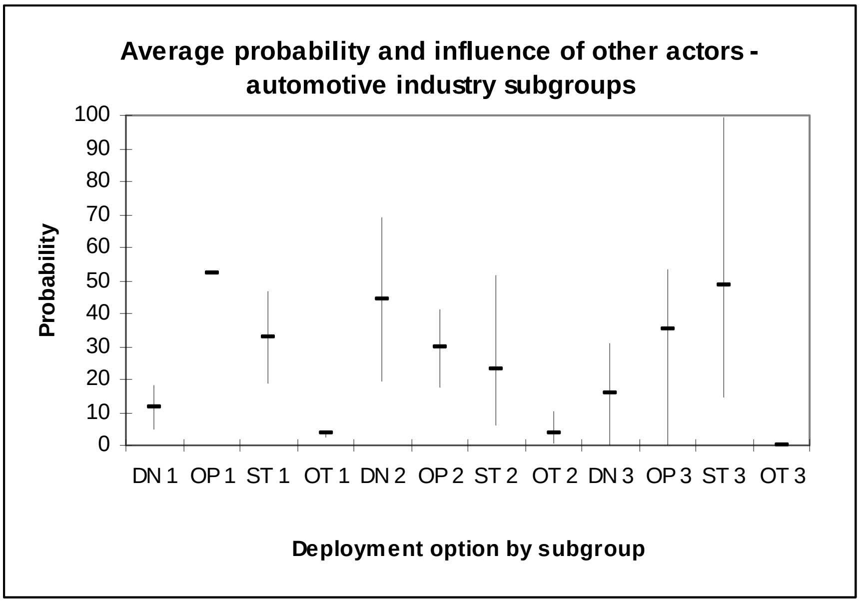


Figure 20 Automotive industry's probability subgroup characteristics.

Automotive industry's probability subgroup 1 (n=25)
The respondents in this subgroup expect it to be most likely that automotive industry takes action, optional deployment being most probable. If authorities mandate deployment, they expect industry to be almost indifferent between optional and standard deployment. This subgroup is interpreted as seeing automotive industry as an *Active Deployer*.

Automotive industry's probability subgroup 2 (n=10)
The respondents in this subgroup expect it to be most probable that automotive industry does nothing, especially when authorities are doing nothing. They expect industry to be almost indifferent between doing nothing and optional equipment if authorities apply tax reduction. Only if authorities mandate deployment, taking action (standard deployment on all vehicles) is more probable than doing nothing. This subgroup is interpreted as seeing automotive industry as a *Reluctant Deployer*.

Automotive industry's probability subgroup 3 (n=10)
The respondents in this subgroup expect it to be most probable that automotive industry takes action, standard deployment being most probable. If authorities are doing nothing or apply tax reduction, optional deployment and doing nothing becomes most probable. If authorities standardize there is no discussion: automotive industry is expected to apply standard deployment. This subgroup is interpreted as seeing automotive industry as an *Adaptive Deployer*.

7.3.6 *Results insurance companies*
The insurance companies' probability models show that their probabilities are quite conservative (see Table 9). Compared to the preference for action shown by the utility models, the probability models show a preference for doing nothing. The probabilities of the different deployment options are not influenced by the ADAS or deployment options of other actors.

Table 9 Insurance companies' overall probabilities to apply ADAS deployment options.

INSURANCE COMPANIES	**Do nothing**		**Option**		**Standard**		**Other**	
Overall probabilities	coeff	*sig*	coeff	*sig*	coeff	*sig*	coeff	*sig*
Constant	47.302	*0.002*	28.572	*0.001*	16.668	*0.011*	7.462	*0.008*
ADAS								
Speed Assistant	0.078	*0.982*	0.954	*0.599*	0.476	*0.868*	-1.509	*0.243*
Congestion Assistant	2.461	*0.508*	-0.952	*0.600*	-2.381	*0.446*	0.874	*0.442*
Safe Driving Assistant	-2.539		-0.002		1.906		0.634	
Industry action								
Do nothing	4.128	*0.312*	-0.476	*0.787*	-1.664	*0.578*	-1.986	*0.164*
Option	-1.826	*0.613*	0.714	*0.689*	-0.004	*0.999*	1.111	*0.351*
Standard	-2.302		-0.239		1.669		0.874	
Authorities' action								
Do nothing	2.934	*0.441*	-1.906	*0.342*	0.952	*0.743*	-1.986	*0.164*
Tax reduction	-2.776	*0.462*	3.571	*0.147*	-1.428	*0.629*	0.634	*0.562*
Mandate	-0.159		-1.666		0.476		1.351	
R Square	0.658		0.753		0.488		0.860	

By means of a cluster analysis, it was investigated if specific subgroups of insurance company respondents with a clearly different opinion could be identified. Two subgroups of insurance company respondents were identified, and their characteristics are summarized in Figure 21. In this figure, the horizontal dashes mark the average probability of a deployment option (i.e. the constant), and the vertical lines mark the range of influence of (mainly) public authorities on the probability. The abbreviations of the deployment options on the horizontal axis should read as DN 1 = Do nothing, subgroup 1. The subgroup characteristic are discussed below.

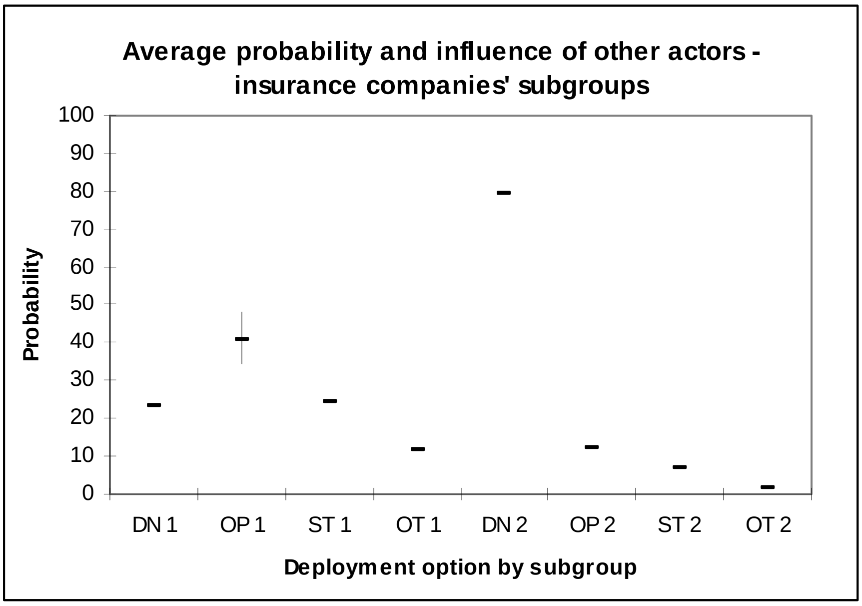


Figure 21 Insurance companies' probability subgroup characteristics.

Insurance companies' probability subgroup 1 (n=4)
The respondents in this subgroup expect the probability of optional premium reduction to be the highest, followed by standard premium reduction and doing nothing having equal probabilities. They expect only minor influence of the other actors on these probabilities. This results in a large probability towards taking action. This subgroup is interpreted as seeing insurance companies as an *Active Deployer*.

Insurance companies' probability subgroup 2 (n=3)
The respondents in this subgroup expect the probability of doing nothing to be the highest, other probabilities are only small. They do not expect any influence of the other actors. This subgroup is interpreted as seeing insurance companies as a *Non-deployed*.

7.3.7 *Conclusions*

Automotive industry is most likely to take action in ADAS deployment
It was found that the probabilities for public authorities and insurance companies were quite conservative, in that they are most likely to do nothing. Since automotive industry is very likely to take action, on average, they could be seen as the most important decision-maker, and to know something about the possible future of ADAS one should study industry decisions. It has, however, to be taken into account that the respondents of automotive industry were predominantly research employees.

Model constants account for most of the probability
For all models the constants were relatively high, showing a focus of the respondents on their own deployment option, while the effects of the ADAS and deployment options of other actors are relatively low.

Many attributes have a low significance: ADAS
In the set-up of the investigation, it was assumed that public authorities would probably take the lead in deployment of the Speed Assistant, automotive industry in deployment of the Congestion Assistant, and insurance companies in the deployment of the Safe Driving Assistant. However, it was found in the results that the ADAS attributes are not

significant most of the times, and if they were their effects on overall utility or probability were relatively small, and would rarely make a difference in the preference for a deployment option. Despite these results, patterns could be observed across the models that do match with the expectations. Though no conclusions can be drawn upon these results, it is an interesting observation, which might be further explored.

Many attributes have a low significance: other actors' deployment options
The expectations regarding the influence of other actors' deployment options on the overall probabilities would be that public authorities will take less action if industry and insurance companies do, and industry takes more action if other actors do. There were no clear expectations on how insurance companies would react on other actors' actions. While the effects are in the expected direction, few of them are actually significant.

In many cases the influence of public authorities and automotive industry on each others' deployment options is significant. However, the influence of insurance companies on the probability of other actors' deployment options is generally not significant, as is the influence of the deployment options of these actors on the probability of insurance company's deployment options.

Subgroups with different strategies exist among the respondents
These results indicate that there are likely different strategies with respect to ADAS deployment present among public authorities, automotive industry and insurance companies.

Automotive industry's subgroups can be distinguished by their preference for deployment options and influence of other actors
Based on the probability data, three subgroups were identified, that expect automotive industry to act as an *Active Deployer* (25 respondents), a *Reluctant Deployer* (10), or an *Adaptive Deployer* (10). The Active Deployer and Adaptive Deployer are most likely to take action as opposed to doing nothing, and this probability is influenced by the deployment options applied by public authorities, with Adaptive Deployers being substantially more influenced than Active Deployers. The Reluctant Deployer is equally likely to apply any deployment options on average, but this strongly depends upon the deployment options applied by public authorities. In general, they are more likely to take action as opposed to doing nothing when public authorities have taken action first.

Insurance companies' subgroups can be distinguished by their preference for deployment options
Both based on the probability data, two subgroups of insurance companies' respondents could be identified, the expect insurance companies to act as an *Active Deployers* (4 respondents), with a preference for taking action, or a *Non-deployer* (3), with a preference for doing nothing. Both groups are not influenced by automotive industry or public authorities. Despite the very small sample, these subgroups are so clearly different that there is enough confidence in their existence.

A possible explanation for the existence of subgroups can be found in the respondents' familiarity with ADAS and their perceptions of the ADAS' impacts
For insurance companies it seems that the more familiar they are with the ADAS, the less positive they expect the impacts are, and the less likely it is that they take action towards ADAS deployment. This seems to be the other way around for automotive industry, the more familiar they are the more positive they expect the impacts and the

more likely they are to take action. To confirm the role of familiarity in the attitude of actors towards deployment, a survey was set up to be performed in conjunction with the professional pilot. In this survey participating actors in this survey would be asked their opinion about deployment of safest route navigation before and after the pilot, presuming they would become more familiar with the system during the pilot. Unfortunately, this survey was hampered by organizational problems during the pilot, the data did not become available. We regret this situation, since it has made it impossible to deliver the results promised in the beginning of the project.

7.4 User survey

The user survey was set up to collect data on the probability that users are going to buy an ADAS on their car, given the deployment options applied by automotive industry, public authorities and insurance companies.

7.4.1 *Survey set-up*

In the survey, respondents were asked to indicate their choice to buy or not buy an ADAS given the type of ADAS, the price, and the insurance premium reduction. The respondents were split in two groups, those who planned to buy a new car in the next two years, and those who were not. For the former the choices applied to buying ADAS as an option on their new car, and for the later the choices applied to buying an ADAS on their current car.

By means of a panel of respondents with a driving licence and a car, a total of 250 reactions were received, of 130 were users that planning to buy a car in the next two years, and 120 were not.

7.4.2 *Model*

The following choice model, a binomial logit model, was estimated using the choice data resulting from the user survey.

The binomial logit model defines the probability $P(C=1|D_1=y)$ that the user chooses to have an ADAS on his car ($C=1$), given that the decision scenario D_1 at time $t=1$ is a certain combination of deployment options y, as a logistic function of the utility V_1 the user attaches to having an ADAS on his car.

$$P(C=1\mid D_1=y)=\frac{1}{1+e^{-V_1}}$$

In which V_1 is represented by an additive utility model:

$$V_1=q+r_0A+\sum_a r_aD_{1,a}$$

V_1 = utility of buying an ADAS
A = ADAS
$D_{1,a}$ = deployment option applied by actor a at time $t = 1$
q = constant of the utility model
r_0, r_a = coefficients of the utility model

The model was estimated using binary logistic regression, and several respondent characteristics were included to explain the variance in the model.

7.4.3 Results

The model presented in this section (see Table 10) represents the utility that private car drivers derive from an ADAS on their new or current vehicle, given certain deployment incentives, and how certain respondent characteristics influence this utility. Regarding the interpretation of the coefficients B in this model, these are the part-worth utilities attached to the variable levels. As a result of the logit model applied, an overall utility of zero corresponds to a 50% probability that the user will buy the corresponding ADAS.

Table 10 Choice model of private car users.

USER MODEL	B	S.E.	Wald	df	Sig.	Exp(B)
Constant	0.136	0.277	0.241	1.000	0.624	1.145
ADAS						
Speed Assistant	-				-	
Congestion Assistant	-0.186	0.120	2.399	1.000	0.121	0.830
Safe Driving Assistant	0.519	0.115	20.342	1.000	0.000	1.680
Cost						
100 euro	-				-	
750 euro	-1.241	0.113	120.199	1.000	0.000	0.289
1500 euro	-1.640	0.122	179.814	1.000	0.000	0.194
Premium reduction						
0%	-				-	
25%	0.644	0.120	28.763	1.000	0.000	1.904
50%	0.854	0.123	47.980	1.000	0.000	2.349
User characteristics						
Age (years)	-0.007	0.004	3.400	1.000	0.065	0.993
Gender (male = 0; female = 1)	-0.209	0.105	3.974	1.000	0.046	0.812
Car use characteristics						
Mileage 0 - 5.000 km = 1 5.000 - 10.000 km = 2 10.000 - 20.000 km = 3 20.000 - 30.000 km = 4 30.000 km and more = 5	-0.110	0.047	5.513	1.000	0.019	0.896
Car characteristics						
ADAS on new or current car ADAS on new car = 0 ADAS on current car = 1	-0.503	0.101	25.085	1.000	0.000	0.604
Car price 0 - 5.000 euro = 1 5.000 -15.000 euro = 2 15.000 - 25.000 euro = 3 25.000 - 35.000 euro = 4 35.000 euro and more = 5	0.209	0.047	19.690	1.000	0.000	1.233
Nagelkerke R square	0.201					
-2 Loglikelihood	2591.920					

Out of the choice attributes ADAS, cost and premium reduction, it can be concluded that the cost of the ADAS has the highest effect on utility. The utility decreases most between 100 and 750 euro, and is, not surprisingly, lowest for 1,500 euro. The influence of premium reduction is smaller but still substantial. The utility increases most between

0 and 25%, which could be interpreted as the presence of a reduction being slightly more important than the height of this reduction. As opposed to what was found for the actors, the different types of ADAS do influence the users' utility. More utility was attached to the Safe Driving Assistants as compared to the Speed Assistant and the Congestion Assistant. However, the latter effect is not significant at the p = .05 level, so the Congestion Assistant and the Speed Assistant actually have a similar effect. The user characteristics entered in the model have a moderate effect on the overall utility. The older the users are the less utility they report to attach to buying an ADAS. The significance of the age effect is 0.065, which means it is exceeding the .05 significance level, but to such a small extent that the direction of the effect is expected to be correct. The second finding relating to user characteristics is that women attach less utility from an ADAS than men.

An interesting finding from the car use characteristics is that the utility of an ADAS decreases with increasing mileage of the user. The explanation for this depends on what users think are the main benefits of ADAS. However, the finding does suggest that the users' confidence in their driving skills or how comfortable they are in driving a car could play a role.

Finally, the car characteristics show that users derive less utility of having an ADAS on their current car than on a new car, and that utility increases substantially with the price of the car. The latter can be explained by the fact that the cost of an ADAS is relatively less when buying a more expensive car, but some other background effects like image or status could also play a role. The cost of the ADAS probably also plays a role in the difference between having an ADAS on a new car or on a current car.

What does this all learn us about the probabilities that users are going to purchase an ADAS? To give an idea, a number of model simulations is performed using the data from Table 10. Nine simulations were made, using combinations of choice attributes and user characteristics leading to the most extremely positive and extremely negative values (except for age: an interval of 25-65 was chosen), and combinations that are in between these extreme values. These simulations are presented in Table 11.

Table 11 Choice probability simulations with user choice model.

		User characteristics		
		man, age 25, 0 – 5,000 km new car: 35,000 euro +	*man, age 45 10,000 – 20,000 km current car: 15,000 – 25,000 euro*	*woman, age 65 3,000 km + current car: 0 – 5,000 euro*
Choice attributes	*Congestion Assistant 1,500 euro no premium reduction*	28.3% (V=-0.930)	9.9% (V=-2.211)	3.9% (V=-3.198)
	Speed Assistant 750 euro 25% premium reduction	57.4% (V=0.299)	27.2% (V=-0.982)	12.2% (V=-1.969)
	Safe Driving Assistant 100 euro 50% premium reduction	90.6% (V=2.269)	72.9% (V=0.988)	50.0% (V=0.001)

Table 11 shows that there is a lot of heterogeneity in the model outcomes, caused by both the choice attributes as well as the user characteristics. This means that the influence of different ADAS and most of all the financial incentives have an important influence on the user's decision to adopt an ADAS. Furthermore, the user characteristics play an important role in this decision, showing that there is a lot of heterogeneity in that respect.

7.4.4 *Conclusions*

Users attach more utility to the Safe Driving Assistant than the Speed Assistant and the Congestion Assistant

A significant difference between the utility user attach to the different ADAS was found, as opposed to what was found as a result of the actor survey. Users were found to attach more utility to buying a Safe Driving Assistant than to buying a Congestion Assistant or a Speed Assistant. This could be caused by the fact that the latter two are more intervening than the Safe Driving Assistant, since user are reported more often to prefer less intervening systems (e.g. Adell et al., 2008, Van Driel and Van Arem, 2005; Marchau et al., 2001).

Financial incentives have a substantial influence on the probability that users will buy an ADAS on their new car

Simulations based on the revised models that, depending on the conditions, the probability that users choose to buy an ADAS on their new car is between 15% and 80%. If the ADAS is the Safe Driving Assistant the probability that users choose to buy an ADAS on their new car is between 31% and 80%, and if the ADAS is the Speed Assistant or the Congestion Assistant this probability is between 15% and 68%. If the cost of ADAS are lowered to 100 euro, this probability is at least 64% for the Safe

Driving Assistant and 50% for the other ADAS. If there is no reduction on the insurance premium, the maximum probability is reduced to 64% for the Safe Driving Assistant and 50% for the other ADAS. Consequently, the cost of the ADAS has a higher impact on the probability that users choose to buy an ADAS than the monthly insurance premium.

It is more likely that car users purchase an ADAS on a new car than on their current car
It was found that the utility of buying an ADAS was higher for respondents that were asked if they would buy ADAS on a new car, than for respondents that were asked if they would buy an ADAS on their current car. Possible causes could relate to the fact that when already spending a certain amount of money on a car, buying an ADAS is a relatively low investment, or the hassle that comes along with having the ADAS installed in a current car.

There is a large heterogeneity among users with respect to the choice for an ADAS
It was found that user, car use and car characteristics – age, gender, mileage, and car price – significantly and substantially influence the probability that a user chooses to buy an ADAS. And since the explained variance of the model is 0.201 (Nagelkerke R^2) is relatively low, there is still a large amount of unexplained heterogeneity in the model, which is probably related to individual preferences.

7.5 Expectations regarding ADAS deployment

Summarizing, what do the results of this investigation learn about the future of ADAS deployment? The most important conclusion is that that automotive industry and public authorities are the main actors and that they are mainly influencing each others' utilities and probabilities to take action. However, the probability of public authorities to take action is expected to be low, and relatively insensitive to what automotive industry is doing. Automotive industry can be expected to take action first, which action depends on the action of public authorities. Insurance companies are relatively insensitive to the actions of other actors, and the other actors are insensitive for their actions. The probability that they will take action is fairly low.

In addition to this general conclusion, what does the knowledge about the subgroups of automotive industry and insurance companies learn us about ADAS deployment? Most important, the automotive industry is heterogeneous with respect to decision-making regarding ADAS deployment. This heterogeneity manifests itself in different preferences for deployment options and susceptibility to influence of (mainly) public authorities. This means that it can be expected that, in first instance, different parts of automotive industry will show different strategies regarding ADAS deployment. Whether specific strategies can be attributed to specific parts of automotive industry could not be clearly determined from the respondent characteristics, possibly the brand image and market visions of different companies plays a role. Based on the subtle findings that automotive industry respondents who are more familiar with ADAS perceive its impacts as more positive and expect a more active role of automotive industry in ADAS deployment, a possible future development could be that when familiarity with ADAS increases, automotive industry is even more likely to drive ADAS deployment.

Insurance companies are not straightforwardly expected to take any action in the near future, while part of the respondents does expect that they will. But, based on the quite clear findings that insurance company respondents who are more familiar with ADAS perceive its impacts as less positive and expect a very inactive role of insurance companies, a possible future development could be that when familiarity with ADAS increases, insurance companies are not likely to play a part in ADAS deployment.

Finally, what does the knowledge about user reactions to actor deployment options learn us about ADAS deployment? Without any specific incentives, and presuming that the price level of an ADAS is indeed around 1,500 euros, the results show that there is a probability of about 15% that users choose to buy a Speed Assistant or Congestion Assistant, and a probability of about 30% that they choose to buy a Safe Driving Assistant. Apparently, users are more interested in informing systems than more intervening systems. But since the effectiveness of informing systems can be lower than for more intervening systems (e.g. Carsten and Tate, 2005), actors like public authorities would require a higher probability of choice, and as a result a higher number of cars equipped, in order to reach their objectives. As such, no conclusions can yet be drawn on whether choice for one type of ADAS needs to be more stimulated than another.

If actors want to stimulate users' choice to buy an ADAS, the results of the user survey shows that applying a reduction on the purchase costs may prove to be more effective than a reduction on the monthly insurance premium. Since the utility of buying an ADAS on a current car is reported to be lower than on a new car, higher incentives may be necessary if there is a need to pursue retrofitting of ADAS.

The reported heterogeneity in the utility users attach to buying an ADAS can be addressed by (mixed) strategies of actors to stimulate the adoption rate in the most effective way. If the objective of the actor is to make profit out of selling ADAS (e.g. automotive industry) they could aim first at target groups with a high probability of choosing to buy an ADAS, and later, when they are able to lower the price, on other groups. If the objective of the actor is to increase traffic safety or reduce congestion (e.g. public authorities), they could stimulate those target groups that are reported to be more accident prone or driving more often in congestion than others, and attach a relatively low utility to buying the ADAS (e.g. speed offenders).

8 Overall conclusions

The aim of the professional pilot was to influence the route choice behaviour of professional drivers by providing a financial incentive for following a safest route. The pilot addressed how this goal can be achieved. Various steps have been taken to address this objective.

In a literature review it was concluded that the relationship between route choice and safety is not often described. Only one study was found, were the focus was on private drivers instead of professional drivers. Therefore, the concept of influencing route choice to a safest route, especially for professional drivers, appeared to be new.

For the theoretical and practical implementation, two different components have been explored. Firstly, a general model for the incentive program was proposed. This conceptual model was used as basis for the model used in the on-line survey and the Field Operational Test. Secondly, the safest route algorithm was described. In the literature, one can find algorithms to determine a fastest route or shortest route. However, ready-to-use algorithms for a safest route were not available. Therefore, the safest route was based on 'Duurzaam-Veilig' criteria as developed by the SWOV. The safety of resulting routes can be assessed in various ways. For completeness an overview of assessment approaches was given.

Subsequently, three studies have been undertaken. The first study was undertaken to assess drivers' response to the incentives and thereby the potential benefit of safest routes, an online before-and-after survey was conducted. This study introduced a route-based incentive program operated by a logistic company together with an insurance company. In total 45 Dutch professional drivers participated in the survey. A win-win situation for the two companies was demonstrated to exist dependent on driver behaviour, the road network, as well as the settings in the incentive program.

The results showed that drivers tend to ignore safety-related information in making their route choices; however, the incentives had a significant effects on these choices. The incentives therefore present an efficient way of influencing drivers' route choices. The online survey used in this study is a stated preference technique to investigate driver behaviour in future situations. When the incentive program is put into practice, the actual driver behaviour (i.e. revealed preference) may differ.

The impact of several assumptions in this study needs to be addressed in follow up studies. In particular, the benefit of the logistic company depends on not only the safety aspects but also other factors such as cost and operation efficiency. If drivers take a longer route because of the incentive program, higher fuel cost is expected which is in the end carried by the logistic company. Due to longer travel time per journey, the number of deliveries that a vehicle can do per day might also be reduced. A more comprehensive cost benefit analysis is therefore necessary from the logistic company's point of view.

The second study was conducted to determine the revealed preference, i.e., whether incentives have a significant effects on the route choice in practice. This study was a Field Operational Test (FOT). During the test, which lasted 2 months, the driving behaviour and route-choice of professional drivers were unobtrusively measured.

The vehicles were equipped with a navigation system, which could generate a fastest and a safest route to a given destination. After one month, the participants were rewarded when they drove the safest route.
The used route algorithms have been compared for a sample of origin-destination points taken from the field operational test. In the comparison between the resulting safest and fastest route, it was found that in 78% of the cases the trips were equal. This result is an important requirement for the sustainable safety principle were one is aiming at both safest routes and fastest routes. For the remaining 22% of the cases, there were differences between the fastest and safest routes. The travelled distance for the safest route was longer compared to the fastest route. The differences were caused by an increase of travelled distance on through roads and access roads.

The FOT did not show a positive effect on the use of an incentive. There are many possible causes that could have an influence on this result. The main point was that both systems differed with respect to functionality and usability. The fastest route algorithm was implemented on the PND whereas the safest route was implemented at a back-office. This had many consequences, such as the required time before the system was ready for use. Therefore, the study did not explore the effect of an incentive on the route choice but rather on the technology used. Secondly, due to various technological set-backs the measuring period of the pilot was reduced multiple times. This affects the effect size. The variance in the outcome decreases when the test time and number of participants decreases, with as result that a possible effect is not identified due to this increased variance. Thirdly, initially the route advice was unrealistic for the safest route option in the without incentive condition. This could have had the effect that participants did not use this route-option again due to the bad experience, even with an incentive. Finally, the driver was not directly rewarded when a safest route was driven. They received there incentive once a month as an addition on their salary.
From literature, we know that directly rewarding a participant has the best effect to influence ones behaviour. Concluding, a follow-up pilot is required to prove the effect of incentives to influence the route choice.

The third study was performed to assess the probability that public authorities, automotive industry and insurance companies are going to apply certain deployment options to influence the user to buy an ADAS, and the probability that users will buy an ADAS given these deployment options. To this end an actor and a user survey were held, using stated preference methodology, to estimate models of actor and user decision making. To the actor survey, 75 reactions were received of which 72 were usable, and to the user survey 250 reactions were received.

In this survey, three different ADAS were considered, for each of which it was expected that another actor would take the lead in deployment. For public authorities, an assisting type of Intelligent Speed Adaptation was considered. For automotive industry, Adaptive Cruise Control combined with Stop&Go was considered. And, for insurance companies, safest route navigation was considered in combination with speed warning and headway warning, including feedback to the driver on how safe his driving is.

Three deployment options were included for each actor, including doing nothing, a stimulation option (tax reduction for public authorities, ADAS as an option on new vehicles for automotive industry, and an optional insurance policy with premium reduction for safe driving), and a forcing option (mandatory equipment with ADAS,

ADAS standard on new vehicles, and a standard insurance policy with premium reduction for safe driving respectively).

The overall results of the actor survey show that automotive industry is most likely to taking action in ADAS deployment, and which action they are most likely to take depends on the deployment options applied by public authorities. Public authorities and insurance companies are most likely to do nothing. There was no significant difference found between the ADAS. A cluster analysis, identifying subgroups of actors with similar deployment strategies, showed that some subgroups of respondents are more likely to taking action and others attach more utility to doing nothing. A possible explanation for the existence of these subgroups was found in the familiarity of the respondents with ADAS, and their perceived impacts of the ADAS. The results would suggest that if all actors are becoming more familiar, automotive industry would attach more utility to taking action, and public authorities and insurance companies would attach most utility to doing nothing. However, these results should be seen as indicative, since the differences between the subgroups were often not significant.

The overall results of the user survey show that if automotive industry offers ADAS as an option for about 1,500 euros, the probability that users would buy the ADAS is about 15% for the Speed Assistant or Congestion Assistant, and 31% for the Safe Driving Assistant. If public authorities apply a 1,500 euro tax reduction, these probabilities can increase to 50% and 64%. Applying a tax reduction has a much smaller effect on this probability. Respondents that were asked if they want to buy an ADAS as an option on their next new car were more likely to do so than respondents that were asked if they want to buy an ADAS on their current car. Furthermore, there is a large heterogeneity among users, which can partly be explained by gender, age, annual mileage and the price of their car.

In summary: A safest route algorithm is developed and implemented. This algorithm is successfully validated. In a survey drivers indicated a willingness to choose a safer route if a reward was given. Unfortunately, the field trial did not provide sufficient evidence that drivers actually drive this safer route. It is also uncertain whether the government or insurance companies are willing to provide incentives.

8.1 Follow Up

STOK aims to take the IV challenge to another level by ongoing development of the technology. Technique is always evolving and larger manufacturers of hardware are becoming more and more interested in value added services.

In addition, the automotive industry, insurers and banks are increasingly interested in ways to anticipate on the individual needs of end-users. Telematics can help them to reach their objectives.

Together with a large telecom provider, STOK will open up discussions with the above mentioned hardware providers and invest in further development of the system in order to create an easy to use and accessible product that can facilitate innovative location based value added services.

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11 Signature

Soesterberg, December 2009

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