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HEC MONTRÉAL

La relation entre la propension au risque, la prise de risque en conduite simulée et ses corrélats neurophysiologiques

par

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(Option Expérience utilisateur)

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Résumé

Un des principaux objectifs des compagnies d’assurance automobile est d’estimer le risque que représentent leurs assurés sur la route; le suivi télématique est un bon exemple de stratégie employée pour estimer ce risque. Néanmoins, cette pratique laisse place à l’amélioration. Ce mémoire envisage la possibilité de pouvoir concevoir des outils simples à implémenter qui pourraient améliorer la capacité de prédiction du risque au volant grâce à la mesure de la propension au risque. Une étude en laboratoire a été effectuée afin d’évaluer le pouvoir prédictif de différentes mesures de propension au risque pour la prise de risque au volant dans une simulation de conduite. Des données neurophysiologiques ont également été collectées pendant la simulation pour déterminer la mesure dans laquelle la prédiction du comportement de conduite pourrait être corroborée par l’activité cérébrale oscillatoire reliée à la prise de risque au volant. Les résultats de l’analyse impliquant le comportement de conduite révèlent que le score global d’un questionnaire mesurant la propension au risque dans différents types de situation a une certaine valeur prédictive pour la prise de risque au volant. Cependant, cette valeur prédictive n’a pas été corroborée par l’activité cérébrale mesurée dans cette expérience. De plus, les mesures objectives de propension au risque (provenant de tâches interactives) n’ont pas démontré de valeur prédictive pour la prise de risque pendant la simulation. Nos résultats suggèrent que, pour la prédiction de la prise de risque au volant, les mesures autodéclarées de propension au risque sont de meilleurs candidats que les mesures objectives du même construit; ce type de mesure présente donc un potentiel intéressant pour le domaine de l’assurance automobile.

- **Mots clés :** prise de risque, propension au risque, prédiction du risque, risque au volant, assurance automobile, télématique, électroencéphalographie, simulation de conduite

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La numérotation des figures et tableaux a été modifiée dans l'article pour faciliter la lecture de ce mémoire.

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Avant-propos

Ce mémoire en expérience utilisateur a été soumis avec l'autorisation de la direction administrative du programme de la Maîtrise ès Science en Gestion.

Le projet de recherche lié à ce mémoire a été approuvé par le comité d'éthique en recherche (CER) de HEC Montréal le 20 février 2019. Un article issu du projet est inclus dans ce mémoire avec le consentement des coauteurs.

L'article est actuellement en préparation pour soumission au journal *Frontiers in Psychology*. Il explore la relation entre la propension au risque, la prise de risque dans un simulation de conduite et ses corrélats neurophysiologiques.

Une partie du projet de recherche a également fait l'objet de la présentation d'une affiche à la conférence annuelle de la *Society for Neuroeconomics* en octobre 2020 (voir Annexe 1).

Remerciements

La réalisation de ce projet et l'écriture de ce mémoire n'auraient pas été possibles sans l'aide et le support de certaines personnes à qui je dois mes plus sincères remerciements.

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Chapitre 1: Introduction

1.1 La télématique et l'assurance auto

Au sens large, la télématique fait référence à la combinaison des télécommunications et de l'informatique. Plus couramment, il est question de télématique lorsqu'un système permet d'acquérir des données générées par un véhicule et de transmettre celles-ci par l'entremise d'un réseau de télécommunications. La télématique dans le contexte des transports est donc une matrice de capteurs, d'instrumentation, de communication sans fil et de technologies GPS qui est employée dans plusieurs domaines d'affaires tels que la gestion de flotte et l'assurance automobile (Handel et al., 2014; Mikulski, 2010; Zhao, 2002).

Dans le domaine de l'assurance auto, des données télématiques concernant la conduite d'un client sont parfois utilisées pour personnaliser l'assurance en fonction des habitudes de conduite. La prime d'assurance est alors périodiquement ajustée en fonction de facteurs de risque tels que la distance parcourue, le moment de la journée où la conduite a habituellement lieu, et la façon dont les freinages et accélérations sont faits (Nedić et al., 2014). Ce concept est généralement appelé « assurance en fonction de l'usage » (usage-based insurance ou UBI en anglais), « assurance télématique » ou « suivi télématique ».

Typiquement, les données concernant la conduite sont acquises de l'une ou l'autre de deux façons. Dans certains cas, un appareil de type boîte noire est installé sur le véhicule, et cet appareil récolte des données pour ensuite les envoyer à l'assureur. Cependant, cette méthode est de plus en plus abandonnée par les compagnies d'assurance; dans la plupart des cas, il n'est plus nécessaire d'installer de tel équipement sur la voiture, car le téléphone intelligent des clients peut jouer un rôle très similaire. Les téléphones intelligents dotés d'un GPS, d'un accéléromètre et d'un gyroscope (donc la plupart d'entre eux) sont en mesure de collecter en continu des données sur la position et la vitesse du véhicule ainsi que son accélération longitudinale (permettant de jauger la façon d'accélérer et de freiner) et latérale (permettant de jauger la façon d'effectuer un virage), en plus de permettre de synchroniser ces données avec l'heure et les conditions de météo et de circulation (Handel et al., 2014). Avec ces données, ces applications peuvent généralement aussi détecter l'utilisation du téléphone mobile au volant (Guillen et al., 2021).

Les compagnies offrant l’assurance en fonction de l’usage ont donc généralement une application mobile qui sert principalement à acquérir et transmettre ces données, mais qui peut aussi offrir d’autres services aux clients tels qu’un tableau de bord sur les habitudes de conduite et des recommandations personnalisées visant une conduite plus sécuritaire (Handel et al., 2014). Les clients inscrits à un tel service obtiennent un ajustement de leur prime d’assurance, soit sous la forme de rabais associés avec de bonnes habitudes de conduite, soit sous la forme de pénalités associées avec une conduite dangereuse (Ma et al., 2018).

1.2 L’assurance télématique au Québec

À l’échelle mondiale, le concept de l’assurance télématique a d’abord été inventé et breveté en 1996 par la compagnie américaine Progressive, qui a ensuite graduellement introduit sa première police d’assurance télématique avec le projet pilote “snapshot” en 1998. En 2016, plus de 2 millions de véhicules étaient assurés à travers “snapshot”, et un total de 3.3 millions de couvertures d’assurance télématique étaient en vigueur aux États-Unis. Les autres pays dominant ce marché sont principalement l’Italie et le Royaume-Uni, qui, en 2016, avaient respectivement 6.3 et 0.6 millions de polices d’assurance télématique en vigueur (Eling & Kraft, 2020).

Au Québec, la première forme d’assurance télématique documentée fut le programme Mobiliz instauré en 2012 par Industrielle Alliance (Bergeron, 2014). Dans ce programme (seulement disponible aux 16-24 ans), une boîte noire était installée à l’intérieur du véhicule, et celle-ci mesurait 4 indicateurs de conduite : le kilométrage, la vitesse, les freinages brusques et les accélérations rapides. À chaque renouvellement de contrat, la prime était déterminée en fonction de certaines limites que le client acceptait de respecter (Radio-Canada, 2015). Il est intéressant de noter que, à cette période, la conseillère aux affaires publiques au Bureau d’assurances du Canada (BAC) avait affirmé : « Ce n'est pas très bien accueilli de mettre un mouchard sur la voiture ». Certains considéraient le procédé comme une atteinte à la vie privée (Templier, 2012). Mobiliz fut le premier programme d’assurance au Québec à exploiter des données sur plusieurs mesures comportementales de la conduite des clients inscrits. Étrangement, le programme fut abandonné en 2017, la compagnie affirmant se donner jusqu’à 2018 pour repenser la formule (McKenna, 2017). À ce jour, le programme n’est toujours pas disponible chez Industrielle Alliance.[1]

[1] https://ia.ca/assurance-auto

En 2013, Desjardins a inauguré son programme Ajusto, qui à l'époque nécessitait aussi l'installation d'une boîte noire branchée à l'ordinateur du véhicule (McKenna, 2017). Cet appareil télématique fut remplacé par une application mobile en 2015 (McQuigge, 2015). En 2017, un sondage effectué par Desjardins auprès des participants au programme a révélé que 75% d'entre eux avaient amélioré leurs habitudes de conduite et que 76% ont dit être d'avis que le programme contribue à l'amélioration de la sécurité routière (McKenna, 2017).

En ce qui a trait au régime public d'assurance auto, la Société de l'assurance automobile du Québec (SAAQ) a exprimé en 2015 l'intention de mettre à l'essai un outil télématique qui permettrait aux conducteurs volontaires de visualiser et d'adapter leur comportement de conduite, en plus d'éventuellement voir le coût de leur permis et de leur immatriculation diminuer en fonction de celui-ci (Radio-Canada, 2015). Cependant, le projet a été annulé l'année suivante par peur de manquer de volontaires (Morin, 2016).

Au fil des années, à Ajusto se sont ajoutés les programmes automérite de belairdirect (en 2013) et Ma Conduite d'Intact (en 2014) (Bergeron, 2014). Ces 3 programmes sont donc à ce jour les seuls au Québec à employer la télématique dans un contexte d'assurance automobile. Le tableau suivant (Tableau 1) fait le sommaire des caractéristiques de ces programmes.

Tableau 1. Sommaire des 3 programmes d'assurance télématique actuellement disponibles au Québec

<table>
<tr><th></th><th>Méthode d'acquisition de données</th><th>Mesures comportementales</th><th>Ajustement du tarif</th></tr>
<tr><td>Ajusto (Desjardins Assurances)</td><td rowspan="3">Application mobile nécessitant un iPhone version iOS 12 ou plus récente, ou un téléphone Android version 7.0 ou plus récente</td><td>Un score de conduite (entre 0 et 100) est calculé après 6 mois et au moins 1000 km. Ce score est calculé en fonction de 4 critères : la distraction causée par le cellulaire, la vitesse, les accélérations rapides et les freinages brusques. Le score prend également en compte les habitudes de conduite : la distance parcourue, les heures de déplacement et la routine quotidienne. Un nouveau score est calculé à chaque renouvellement.</td><td>• 10% de rabais pendant les 6 premiers mois

• Un score en haut de 60 peut entraîner une baisse de prime pouvant aller jusqu'à 25%, alors qu'un score en bas de 60 peut la faire augmenter jusqu'à 20%.

• La prime est ajustée à chaque renouvellement du contrat d'assurance.</td></tr>
<tr><td>Ma Conduite (Intact)</td><td rowspan="2">Les mesures suivantes sont prises en compte après au moins 500 km de conduite: la vitesse, la fluidité (des freinages et accélérations), la vigilance (l'utilisation du téléphone au volant), la distance parcourue, le moment de la journée, l'endroit et la fréquence de conduite. Ces mesures sont prises en compte à chaque renouvellement de contrat.</td><td rowspan="2">• 10% de rabais jusqu'au prochain renouvellement de contrat (seulement pour les nouveaux clients)

• Le comportement de conduite peut mener à une baisse de prime allant jusqu'à 25%, ou une augmentation pouvant aller jusqu'à 25%.

• La prime est ajustée à chaque renouvellement du contrat d'assurance.</td></tr>
<tr><td>automérite (belairdirect)</td></tr>
</table>

Sources: https://www.desjardins.com/qc/fr/assurances/auto/ajusto.html, https://www.desjardins.com/qc/fr/assurances/faq/ajusto.html, https://www.intact.ca/fr/assurance-particuliers/services-en-ligne/ma-conduite.html, https://www.intact.ca/qc/fr/assurance-particuliers/services-en-ligne/ma-conduite/faq.html, https://www.belairdirect.com/fr/app/automerite.html, https://www.belairdirect.com/fr/app/faq.html?region=qcfr

1.3 L’estimation du risque au-delà de l’assurance télématique

L’évolution du marché de l’assurance télématique au Québec démontre que de nombreuses compagnies se tournent vers le téléphone mobile comme outil d’acquisition et de transmission de données sur le comportement de conduite d’utilisateurs assurés. En plus d’être simple, peu coûteuse et facile à personnaliser comparée à l’utilisation d’un appareil de type boîte noire, cette formule permet d’exploiter les nombreuses fonctionnalités d’une application mobile, comme la présentation d’un tableau de bord pouvant informer l’utilisateur sur sa conduite et faire des recommandations pour la rendre plus sécuritaire. Néanmoins, cette formule comporte aussi des limites. D’un point de vue technologique, il est difficile d’assurer la précision et l’intégrité de données télématiques provenant d’un téléphone intelligent (Handel et al., 2014)**;** un bref coup d’oeil aux commentaires écrits sur Google Play Store par les utilisateurs d’applications d’assurance télématique en fonction au Québec révèle qu’un grand nombre d’entre eux rapportent des difficultés quant à l’acquisition de données (p.ex. la conduite n’est pas toujours détectée et suivie automatiquement), le signalement erroné de manœuvres dangereuses et la consommation excessive de la batterie du téléphone. De plus, il semblerait qu’un grand nombre d’individus soient réticents à l’idée d’être constamment suivis par leur assureur lorsqu’ils sont au volant, comme le suggère le motif du recul de la SAAQ quant à son projet pilote de télématique (Morin, 2016).

Un besoin important auquel répond l’assurance télématique est celui des compagnies d’assurance de pouvoir estimer dans une certaine mesure la probabilité qu’un client soit impliqué dans un accident de la route. L’assurance télématique, qui de plus en plus s’appuie sur le téléphone intelligent, comporte des limites importantes qui restreignent sa capacité à répondre à ce besoin pour un grand nombre de clients. Le projet présenté dans ce mémoire envisage la possibilité de pouvoir concevoir des outils simples à implémenter pouvant aider à répondre à ce besoin. Par exemple, serait-il possible de concevoir des applications qui estiment adéquatement la propension au risque au volant de sorte à pouvoir mieux prédire ce risque?

1.4 Questions de recherche et sommaire de l’article

Plusieurs outils de mesure du risque ont été développés dans les dernières décennies, et leur succès porte à croire qu’il pourrait être possible d’employer un tel outil pour améliorer notre capacité à prédire le potentiel de prise de risque au volant. Ce projet vise donc à tester cette idée; nous mesurons la capacité prédictive de certains outils de mesure du risque par rapport à la prise de risque au volant dans un simulateur de conduite en laboratoire. Nous mesurons donc la performance et le score à certains outils de mesure du risque, ainsi que certaines composantes du comportement de conduite pendant la simulation. De plus, dans le but de fournir un support théorique à notre analyse, nous mesurons également l'activité neurophysiologique (par électroencéphalographie) pendant les moments risqués de la simulation de conduite pour déterminer la mesure dans laquelle le pouvoir prédictif potentiel de ces outils se reflète dans l'activité cérébrale reliée à la prise de risque au volant.

Ce mémoire répond donc à deux questions de recherche. D'une part, l'analyse comportementale répond à la question suivante: *Dans quelle mesure est-il possible de prédire la prise de risque dans une simulation de conduite à l'aide d'outils mesurant la propension au risque*[2]*?* Pour se faire, la prise de risque pendant la simulation est opérationnalisée à l'aide de plusieurs variables relatives au comportement de conduite des participants; ces variables sont très similaires aux mesures employées par les programmes d'assurance télématique présentés dans ce chapitre. Des modèles de régression multivariée sont ensuite employés pour déceler de potentielles associations entre les scores provenant des outils de mesure du risque et le comportement de conduite. D'autre part, l'analyse impliquant les données neurophysiologiques répond à la question suivante: *Dans quelle mesure est-il possible de prédire l'activité cérébrale oscillatoire reliée à la prise de risque dans une simulation de conduite à l'aide d'outils mesurant la propension au risque?* Pour isoler des signaux neurophysiologiques reliés à la prise de risque pendant la simulation, les signaux provenant des sections définies comme risquées dans le trajet de la simulation sont normalisés avec ceux provenant des sections impliquant un minimum de risque. Des modèles de régression multivariée sont ensuite employés pour déceler de potentielles associations entre les scores provenant des outils de mesure du risque et les moyennes obtenues suite au traitement, à l'agrégation et à la normalisation de ces signaux neurophysiologiques.

Ce mémoire comprend un seul article qui présente en détail l'expérience en laboratoire brièvement décrite ci-dessus—une expérience ayant eu lieu au Tech3Lab et impliquant 18 participants

[2] Dans ce mémoire, la propension au risque et la préférence face au risque sont utilisées de façon interchangeable. Elles représentent la propension à effectuer des choix ou des actions considérées comme risquées, peu importe la nature des risques impliqués.

volontaires. Cet article est en préparation pour soumission au journal *Frontiers in Psychology*. La première partie de celui-ci fait le sommaire d'une revue de littérature sur la mesure de la propension au risque (et la préférence face au risque) ayant été effectuée dans le but de déterminer quels outils de mesure sont les meilleurs candidats pour la prédiction de la prise de risque au volant. La deuxième partie de l'article présente en détail la méthodologie employée et les résultats obtenus. Ces résultats sont ensuite interprétés et discutés en fonction de la littérature académique concernée. Finalement, la dernière partie de l'article ainsi que la conclusion du mémoire présentent les implications pratiques et théoriques des résultats de ce projet.

En outre, une analyse préliminaire des données collectées dans le cadre de ce projet a fait l'objet de la présentation d'une affiche (*poster presentation*) par l'auteur de ce mémoire lors de la conférence annuelle (virtuelle) organisée par la *Society for Neuroeconomics* en octobre 2020. Cette affiche présente seulement l'analyse des données comportementales et neurophysiologiques de la *Iowa Gambling Task* et de la simulation de conduite (voir Annexe 1).

1.5 Contributions et responsabilités individuelles

Le tableau suivant (Tableau 2) rapporte les contributions de l'auteur tout au long du processus menant à la réalisation de ce mémoire. Pour chaque étape du projet, la ou les tâches effectuées sont présentées avec la contribution (en pourcentage) de l'auteur de ce mémoire.

Tableau 2. Tableau des contributions

Activité	Contribution
Définition de l'objectif de recherche	Définir l'objectif de l'étude et les questions de recherche associées - 60% Les questions de recherche sont issues de nombreuses discussions avec l'équipe de recherche.
Revue de littérature	Faire d'abord un survol de la littérature, puis une recherche approfondie sur les différentes méthodes de mesure du risque - 100%
Conception du design expérimental et préparation de l'étude	Choisir les outils de mesure du risque employés dans l'étude - 100% Choisir le logiciel de simulation de conduite approprié, ainsi que les paramètres à utiliser dans celui-ci - 70% Ce choix fut effectué en collaboration avec l'équipe de

	recherche. Effectuer la demande au CER - 100% Un membre de l'équipe d'opération du Tech3Lab s'est assuré que le formulaire était adéquat. Concevoir les tâches de prise de risque dans le logiciel E-Prime et programmer la synchronisation en temps réel des données avec le logiciel d'électroencéphalographie - 90% L'équipe de recherche a aidé l'auteur de ce mémoire à régler certains problèmes rencontrés lors de tests sur la synchronisation des données. Concevoir la tâche de conduite de sorte à ce qu'elle permette de répondre aux questions de recherche - 60% Cette tâche fut conçue en collaboration avec l'équipe de recherche. Concevoir et rédiger le protocole de l'expérimentation - 100% Un membre de l'équipe d'opération du Tech3Lab s'est assuré que le protocole expérimental était adéquat.
Collecte de données	Installer l'équipement dans la salle de collecte - 80% Un membre de l'équipe d'opération du Tech3Lab a aidé l'auteur de ce mémoire à installer le matériel de collecte. Effectuer des prétests pour s'assurer du bon fonctionnement de tous les outils, de la bonne synchronisation des données, de la fluidité de l'expérience et de la qualité des données - 100% Un assistant de recherche du Tech3Lab a contribué à la collecte de données pendant tous les prétests. Élaborer et rédiger le questionnaire de recrutement - 100% Recruter les participants et gérer les prérequis avant chaque collecte - 80% Le recrutement fut en partie effectué par l'entremise du Panel HEC Montréal. Collecter les données - 100% L'auteur de ce mémoire fut présent à chaque collecte de données. Un assistant de recherche du Tech3lab fut également toujours présent pour aider et veiller au bon fonctionnement des outils de collecte de données.

Extraction et transformation des données	Extraire les données comportementales des tâches de prise de risque et de la tâche de conduite, ainsi que les données neurophysiologiques - 100% Élaboration d'un script Python pour extraire et faire les moyennes des données comportementales de conduite provenant des moments clés de la tâche - 100% Nettoyage, agrégation, traitement et transformation des données neurophysiologiques - 100% L'équipe de recherche a formé l'auteur de ce mémoire sur l'utilisation de l'outil Brainstorm, ainsi qu'aidé à l'élaboration d'un protocole de nettoyage des données neurophysiologiques et d'une stratégie de normalisation de ces données. Création d'une base de données commune - 100%
Analyse et interprétation des données	Effectuer les analyses statistiques sur les données comportementales et neurophysiologiques - 100% L'équipe de recherche a aidé l'auteur de ce mémoire à déterminer les modèles statistiques appropriés pour ces analyses. Interpréter les résultats - 100%
Rédaction	Écrire l'article du mémoire - 100% L'article a été écrit avec les commentaires et conseils des coauteurs.

Chapitre 2: Article

Exploring the relationship between risk preference, risky driving in a simulator and the associated oscillatory brain activity[3]

Éric De Celles, Alexander Karran, Jared Boasen, Pierre-majorique Léger, Sylvain Sénécal

Abstract

Risky driving represents a major public safety concern and has been associated with psychological traits such as risk preference. To further our understanding of this behavior as well as our ability to prevent it, this study aimed to investigate the predictive validity of three psychological instruments for risk preference with respect to risky driving in a simulator and the associated oscillatory brain activity. The trait was measured by having participants complete two standardized risk-taking tasks—the Iowa Gambling Task (IGT) and the Balloon Analogue Risk Task (BART)—in addition to the Domain-Specific Risk-Taking (DOSPERT) scale. Risky driving was operationalized using four behavioral measurements in a driving simulation task that encouraged subjects to take risks at the wheel. Electroencephalography was employed to observe neural correlates of risk preference in the oscillatory brain activity of participants during specific parts of the driving task. We found that the DOSPERT scale as a whole predicted risky driving behavior to a significant extent, but that the individual DOSPERT subscales, the IGT and the BART did not. The association between the global DOSPERT score and risky driving was not supported by neurophysiological evidence. Together, our results support the idea that risk preference measurements based on self-reports do not measure the same components of risk-taking as those based on objective assessments, and suggest that the components they measure more closely mirror those involved in risky driving. While more research is needed to investigate this proposition and to uncover the neurophysiological manifestation of risk preference in a driving context, these findings have significant implications for both future research and organizations concerned with the prediction and prevention of risky driving.

[3] Cet article est en préparation pour soumission au journal *Frontiers in Psychology*.

- **Keywords :** Risk taking, Risk preference, Risky driving, Driving simulation, Spontaneous EEG, Balloon Analogue Risk Task, Iowa Gambling Task, Domain-Specific Risk Taking scale

2.1 Introduction

While modern advancements in technology have allowed us to make cars safer than ever before (thanks to systems such as automatic emergency braking, pedestrian detection and blind spot warning), they also take forms that can be detrimental to driving safety; smartphones, smartwatches and certain infotainment systems such as Mazda Connect or Ford Sync are notable examples that can lead to distracted driving (Brodeur et al., 2021; McEvoy et al., 2005; Strayer et al., 2017), a behavior that kills about 8 people every day in the United States (National Center for Statistics and Analysis, 2020).

The issue of distracted/risky driving through the use of technology is multi-faceted; aside from the possession of technology itself, various factors can contribute to an individual's tendency to use distracting devices while driving.

One common trait that has been associated with instances of risky driving is a preference for risk. In psychology, risk preference is usually studied as risk-taking propensity—the propensity to engage in potentially rewarding behaviors or activities despite a potential for loss (Mata et al., 2018). A high preference for risk has been associated with risky driving behaviors such as mobile phone use at the wheel (Sween et al., 2017), more frequent drink-driving amongst older males (Hatfield & Fernandes, 2009), and a higher frequency of speeding in drivers aged 17-20 (Machin & Sankey, 2008). Certain risk preference measurements thus have predictive validity for risky driving behavior, and could potentially serve not only public safety through the implementation of personalized risk countermeasures, but also any organization interested in predicting or preventing risky driving.

However, in both academic and nonacademic sectors, risk preference is rarely assessed to forecast risky driving and its likelihood; in the scientific literature, very few studies have investigated the predictive validity of risk preference for objective measures of real-world outcomes (Mata et al., 2018), and, to our knowledge, the practice is far from prevalent in organizations concerned with the incidence of risky driving such as insurance companies and public safety agencies. The main underlying causes are presumed to be the following. Risk taking itself is not a single trait but an exceptionally complex behavior modulated by a variety of factors, and can thus be exhibited in numerous different ways and contexts (Figner & Weber, 2011). This idea is substantiated by the fact that established measures of risk preference have relatively low convergent validity (Mata et al., 2018), meaning that what they measure does not often seem to capture a common underlying characteristic or trait. In addition, little is known about how all the cognitive processes involved in risk taking interact to form a person's propensity for risk on the road. It is thus not surprising that a psychological instrument with significant predictive validity for objective measures of risky driving remains unheard of. The present study's main objective was to find such an instrument, and investigate its relationship with risky driving objectively assessed in a simulated driving task.

One way to provide support for the predictive validity of a measure (or a construct) is to find neurophysiological evidence of the involvement of at least one relevant cognitive process in mediating a correlation between the measure and a behavior of interest. Such evidence can then be used to formulate a theoretical account of the correlation that is consistent with prevailing theories of cognition and that hopefully generalizes to most healthy individuals. This study draws upon this idea by employing electroencephalography to find such evidence. Therefore, its goal was to find a risk preference instrument with predictive validity for risky driving behavior in a simulator, in addition to neurophysiological evidence that supports this validity.

Our study thus investigated potential associations between three measures of risk preference, risky driving behavior in a simulator, and the associated oscillatory brain activity. Risky driving behavior was operationalized using 4 behavioral variables assumed to be significantly associated with an increased risk of accident. To determine the most appropriate psychological instruments for the purposes of this study, a review of the literature pertaining to the measurement of risk preference was carried out—it is summarized in the next section. During the experiment, subjects first completed the Iowa Gambling Task (IGT) and the Balloon Analogue Risk Task (BART), after which they performed a short driving simulation that encouraged risky driving behavior. At the end of the experiment, the Domain-Specific Risk-Taking (DOSPERT) scale was filled out. EEG signals from specific segments of the driving simulation were captured, normalized to isolate activity specific to risky driving, and time-frequency decomposed in the theta, alpha and beta frequency bands. The resulting data was analyzed in an exploratory manner to find associations between the measures of risk preference and oscillatory patterns of brain activity—during driving—that are consistent with risk-taking behavior, which would further support the predictive validity of said measures.

2.2 Risk preference and predictive validity for risky driving

In the early days of modern psychology, most studies fell into one of two research streams originally identified as experimental and correlational psychology (Cronbach, 1957). While the former put emphasis on rigorously investigating the influence of controlled variables on behavior, cognition and emotion, the latter instead focused on observing and assessing already existing variations in these capacities across individuals and situations. This distinction was often reflected in the measures employed in research; experimental psychology studies usually relied on objective measures as outcomes of interest, whereas correlational psychology studies tended to acquire data in the form of self-reports.

Several decades later, this partition of psychology into two research streams is still discernible (Tracy et al., 2009), but particularly evident in research on risk preference (Appelt et al., 2011; Frey et al., 2017; Hertwig et al., 2019). On one hand, a behavioral stream of research focuses on elucidating the cognitive or neural correlates of risk preference; this work usually investigates the psychological processes underlying choices in very specific behavioral paradigms that tend to feel factitious and hardly naturalistic. The assessments of risk preference derived from such paradigms are often referred to as *revealed* measures of risk preference. One the other hand, a large body of research instead builds upon findings from self-reports related to either risk preference (or propensity) in response to hypothetical scenarios or general questions, or the frequency of actual risky activities such as gambling. The resulting assessments are thus commonly referred to as *stated* risk preference measures.

A persistent concern in the field is that the behavioral and self-report approaches to assessing risk preference have seen very little theoretical and even empirical integration, despite both being widely used to this day (Frey et al., 2017). In addition, recent analyses have shown that stated risk preference measures, when compared to behavioral paradigms, appear to have higher test-retest reliability, higher convergent validity, and even higher predictive validity for certain behaviors

(Frey et al., 2017; Hertwig et al., 2019; Mata et al., 2018). While this trend could warrant the use of only stated measures in this study, it does not for two reasons. First, while supported by compelling evidence, this trend has yet to be empirically confirmed across a variety of contexts, as well as integrated with current theories of decision making. Second, and more importantly, the fact remains that there is substantial evidence in the literature that supports the predictive validity of revealed measures of risk preference for a variety of risky behaviors (Schonberg et al., 2011). The present study being mainly concerned with the predictive validity of risk preference measures, both types described here were considered. In the rest of this section, we thus provide a brief overview of both revealed and stated measures of risk preference used in behavioral research, and discuss their relevance to the purposes of this study in order to select the most appropriate few.

2.2.1 Revealed risk preference measures

The assessment of revealed risk preference is achieved using behavioral paradigms that involve making choices or decisions in specific scenarios comprising risk that is usually economic in nature. Such paradigms often take the form of gamble-like games or tasks that have specific incentive structures and choice architectures. In the last two decades, numerous paradigms have been used to measure revealed risk preference with some degree of success, characterized either by predictive validity for risky behavior, correlations with traits associated with risk preference or propensity, and/or consistency with prevailing theories of risky decision making.

Our review revealed that the most widely used measures of revealed risk preference, which all involve monetary gambles, are the Balloon Analogue Risk Task (BART) (C. W. Lejuez et al., 2002), the Iowa Gambling Task (IGT) (Bechara et al., 1994), the Columbia Card Task (CCT) (Figner et al., 2009), the Cambridge Gambling Task (CGT) (Rogers, 1999), the Holt-Laury (HL) measure of risk aversion (Holt & Laury, 2002), the Gneezy and Potters elicitation method (Gneezy & Potters, 1997), and the Eckel and Grossman elicitation method (Eckel & Grossman, 2002).

While all of these decision-making tasks allow the assessment of revealed risk preference, the purposes for which they were created vary. For example, the IGT was created as a clinical instrument to assess decision making in patients with prefrontal lesions; the BART was specifically designed to measure individual differences in general risk-taking propensity; and the HL task was developed within the economics literature to estimate the risk aversion of economic agents as well as risk parameters of utility functions. Nevertheless, the purpose of the present study being the prediction of risky driving, behavioral measures were only further reviewed for their relevance to this behavior. A revealed risk preference measure was considered a good candidate for this study if it has been shown to correlate with both psychological determinants of risky driving as well as self-reports or observations of risky driving behavior.

The psychological determinants of risky driving have been studied extensively (Tao et al., 2017). While a large number of traits have been linked to various risky driving behaviors (e.g. speeding, aggressive driving, accident involvement), there is considerable support for associations between risky driving and sensation seeking, impulsivity, driving anger, neuroticism, and agreeableness (Akbari et al., 2019; Bıçaksız & Özkan, 2016; Brown et al., 2016; Tao et al., 2017).

Among the measures of revealed risk preference mentioned in this section, two are considered to be good candidates for the prediction of risky driving in this study: the Balloon Analogue Risk Task and the Iowa Gambling Task. The number of pumps on the BART was found to be associated with objective measures of risky driving in a simulator (Ba, Zhang, Salvendy, et al., 2016), multiple self-reports of risky driving (Ba, Zhang, Peng, et al., 2016; Piccardi et al., 2021; Vaca et al., 2013), as well as having a history of traffic offenses on a motorcycle (Cheng et al., 2012). The same score was also found to be correlated with psychological traits related to risky driving such as sensation seeking, impulsivity, and neuroticism (Grover & Furnham, 2021; Lauriola et al., 2014). Regarding the IGT, the number of advantageous decisions was found to be associated with objective measures of risky driving in a simulator (Farah et al., 2008), self-reports of driving violations (Ba, Zhang, Peng, et al., 2016), and having a history of traffic offenses (Brown et al., 2016; Lev et al., 2008). Performance on the IGT is also known to be linked to sensation seeking, impulsivity and neuroticism (Buelow & Suhr, 2013; Denburg et al., 2009; Sweitzer et al., 2008)**.** To our knowledge, performance on the other tasks listed in this section has not been linked to risky driving behavior.

For this study, we chose to include both the BART and the IGT as measures of revealed risk preference, mainly because they are both good candidates for the prediction of risky driving, but also because they have been shown to measure different aspects of decision making based on a factor analysis performed by (Buelow & Blaine, 2015), which could make a difference in their ability to predict risky driving behavior in this study—a difference that could potentially provide insights on the predictors of risky driving.

2.2.2 Stated risk preference measures

The assessment of *stated* risk preference relies upon people's introspective abilities rather than observable behavior. There are three main types of stated risk preference measures: those based on self-reported risk preferences in response to hypothetical or real-world behaviors and scenarios, those based on responses to general questions about people's risk propensity, and those that inquire about the actual frequency of specific risky activities in the life of individuals (Hertwig et al., 2019). The latter, commonly referred to as frequency measures of risk, tend to be used in clinical and epidemiological studies interested in the long-term effects of risky behaviors (Frey et al., 2017), and are mostly absent in the literature related to the construct of risk preference because they generally do not determine an individual's overall risk preference. For this reason, the following review covers only the first two types of stated risk preference measures.

While a large number of self-reported measures have been used to assess risk preference and propensity in the last 50 years, our review focused on the more recent ones that have been validated and correlated with risky behaviors and traits related to risk taking. The most widely used measures of stated risk preference that fit this category are the Domain-Specific Risk-Taking (DOSPERT) scale by (Weber et al., 2002), the Risk Taking Index by (Nicholson et al., 2005), the Risk Propensity Scale by (Meertens & Lion, 2008), the general and domain-specific risk items used in the German Socioeconomic Panel (Dohmen et al., 2011), and the more recent General Risk Propensity Scale (GRiPS) by (Zhang et al., 2019).

The above list comprises two main types of measures: domain-specific and domain-general measures. While a domain-general risk-taking measure aims to assess risk preference as one general dispositional trait, domain-specific risk measures are instead designed to assess risk preference in multiple domains. This distinction is the object of a long-standing debate in the field. Traditionally, many researchers considered risk preference to be domain-specific (Figner & Weber, 2011, p. 20; Hanoch et al., 2006), which is reflected in how individuals vary in their perceived risk and benefit in different domains of situations (e.g. social, financial, health), and have different subjective values on the outcomes. However, recent studies have since challenged this idea by showing that, despite domain differences in risk preference, a general risk factor exists and accounts for variance that is shared across domains (Frey et al., 2017; Highhouse et al., 2017). To this day, no consensus has been reached regarding which theory prevails and yields the most accurate measures of risk preference; the answer likely depends on the context and the purpose of the measurement (Zhang et al., 2019). The present study being exploratory in nature, it was deemed relevant to obtain both domain-general and domain-specific measures of stated risk preference.

Regarding the potential predictive validity of stated measures of risk preference for risky driving, only one was considered to be a good candidate: the Domain-Specific Risk-Taking scale. This scale's global score (all domains combined) was found to be associated with risk taking in a motorcycle simulation (Baltruschat et al., 2020). In addition, scores for individual domains such as health/safety, recreational, ethical and gambling were associated with having a history of traffic offenses (Padilla et al., 2018), in addition to self-reports of speeding, seat belt non-use, and mobile phone use at the wheel (Brailovskaia et al., 2018; Sween et al., 2017; Szrek et al., 2013). To our knowledge, no other measure of stated risk preference mentioned in this section has been linked with self-reports or observations of risky driving.

The DOSPERT was thus selected as the stated risk preference measure of choice for this study because it has been associated with risky driving behavior in several studies, and because it provides a domain-general measure as well as domain-specific measures of risk preference.

2.3 Materials and methods

2.3.1 Experimental design

This laboratory experiment employed a correlational design to investigate the relationship between risk preference—measured through different means—and both behavior and brain activity associated with decision making under risk while driving. Risk preference was quantified using two computerized tasks as well as a psychometric scale. Naturalistic decision making under risk was manifested in a driving simulation task that was specifically designed to encourage risky driving; it motivated risk-taking behavior by offering financial rewards for achieving increasingly difficult task goals that ultimately required faster driving. Brain activity during risky portions of the driving task was recorded, along with driving telemetry. Telemetry was used to operationalize risky driving behavior, and neurophysiological data allowed for an exploratory analysis aimed to investigate the extent to which potential associations between risk preference and driving behavior were reflected in brain activity.

2.3.2 Participants

Eighteen right-handed participants (aged 20-39, $\underline{x}$ = 24.6, SD = 4.0; 6 females) were recruited for the study through our university's research panel. In addition to having no history of neurological disorders, as well as normal or corrected-to-normal vision, all participants were required to hold a valid driver's license and to wear appropriate driving footwear on the day of their participation. This project was approved by our institution's ethics committee (project # : 2019-3443). Participation was thus voluntary, and written informed consent was obtained from all participants before the experiment. Regardless of whether participants successfully achieved the aforementioned difficult driving task goals, all ultimately received a monetary compensation in the form of a $50 gift card from the university's bookstore.

2.3.3 Experimental tasks - Iowa Gambling Task

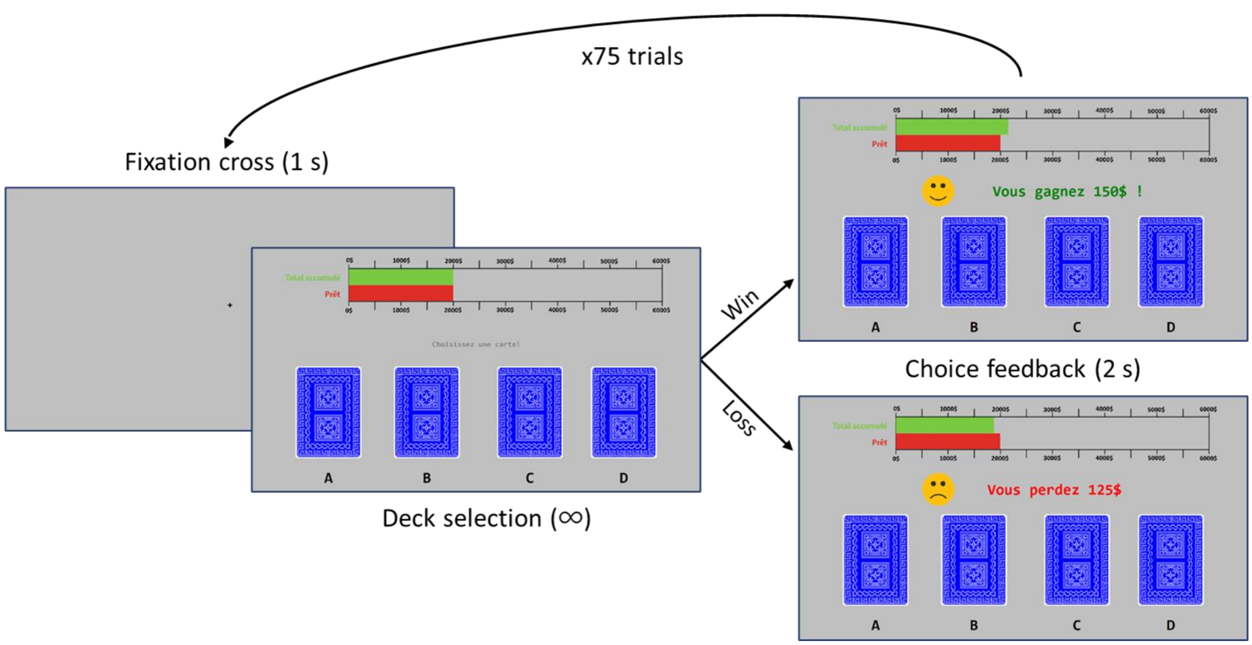

Figure 1. Single IGT trial timeline (Bechara et al., 1994). The task was translated into French.

The first computerized risk task, the Iowa Gambling Task, consisted in a slightly modified version of the original IGT from (Bechara et al., 1994). It differed from the original in that it was adapted for computer presentation, comprised fewer trials (75 instead of 100) to accommodate time for the other tasks of this experiment, and was translated into French. The IGT's goal is to maximize the profit from an initial loan of $2000 through gambling, which requires a long series of selections from four decks of cards—each card draw resulting in monetary gain or loss.

During this portion of the experiment, participants were thus presented with 4 computerized decks of cards (labeled A, B, C and D), from which they were required to successively choose cards—one at a time—using a mouse. Each selection was immediately followed by a display of a monetary reward (win) or a penalty (loss), below an updated loan balance gauge. This choice feedback display stayed on the screen for 2 seconds. It was next replaced by a 1-second fixation cross, which preceded every trial. Decks then reappeared, and participants could make another pick. The whole task was self-paced and only ended once 75 selections were made.

Throughout the IGT, economic outcomes are predetermined: the schedule of rewards and penalties employed here reproduced the original gain-loss structure employed by (Bechara et al., 1994). In this structure, each deck is associated with a specific gain-loss frequency resulting in two main patterns of outcome: decks A and B yield immediate rewards but carry great economic losses in the long run, while decks C and D yield frequent small wins and smaller long-term penalties, resulting in long-term gain. Therefore, C and D are considered to be "advantageous" decks, while A and B are instead referred to as "disadvantageous" decks.

As per the original instructions from (Bechara et al., 1994), participants were initially informed that they could choose freely from any decks as well as alternate among decks; they were also not told how many selections they would have to make. To ascertain a good understanding of the task, participants first went through a short 5-trial version that did not have a specific payoff schedule.

The conventional behavioral metric derived from the IGT is the number of advantageous choices (draws from decks C and D) minus the number of disadvantageous choices (draws from decks A and B) over all 100 trials, also known as the IGT performance index (Bechara et al., 1994). However, recent studies suggest that only later selections (trials 40+) involve decisions under risk, and that early trials should be considered as involving ambiguity rather than risk, due to lack of knowledge about task contingencies during so-called pre-learning trials (Brand et al., 2007; Gansler et al., 2011). In addition, previous studies focusing on the relationship between choice behavior in the IGT and a person's propensity for risk only observed a link between the two after post-learning trials (40+) (Brand et al., 2007; Upton et al., 2011; Xu et al., 2013). For the above reasons, the IGT performance index over trials 40-75 was the chosen measure of risk preference for this portion of the experiment.

2.3.4 Experimental tasks - Balloon Analogue Risk Task

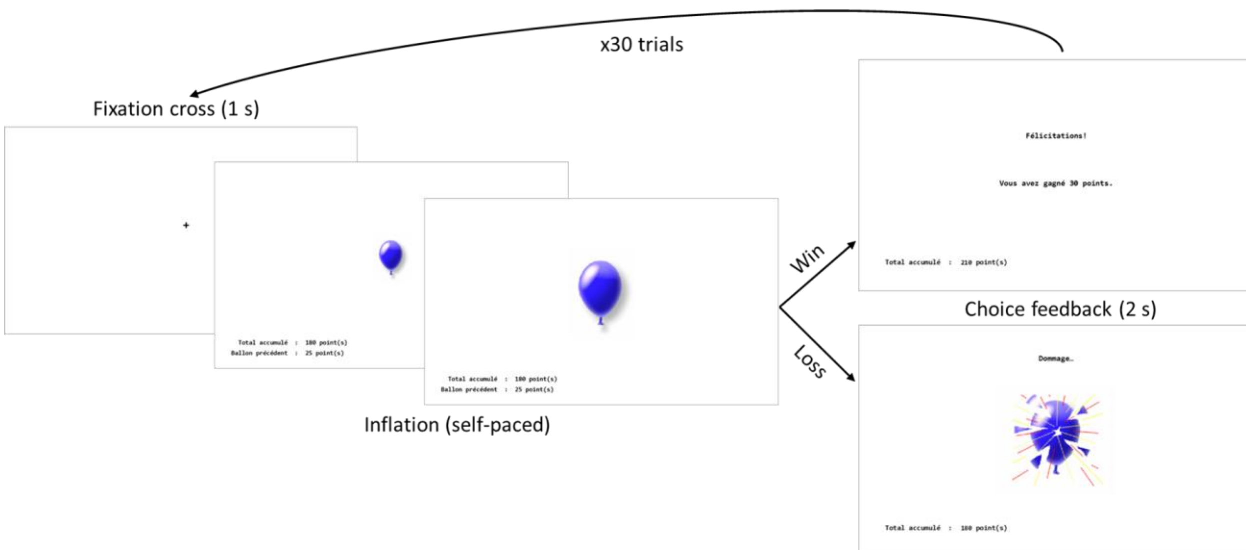

Figure 2. Single BART trial timeline (C. W. Lejuez et al., 2002). The task was translated into French.

The second computerized risk task, the Balloon Analogue Risk Task, was designed based on the original version suggested by (C. W. Lejuez et al., 2002), and translated into French. The BART's goal is to earn as much money as possible by inflating—one at a time—a series of balloons displayed on a computer screen (see Figure 2). The larger a balloon is inflated, the more money can be earned from it. Naturally, its probability to burst at the next inflation also increases with size. The reward associated with a balloon is only earned when the balloon hasn't burst yet and the participant chooses to stop inflating it and collect the money. This implementation of the BART differed from the original in two aspects. First, the task contained only 30 trials of one "type" of balloon. (C. W. Lejuez et al., 2002) used three types of balloons (30 trials of each) characterized by different average bursting points. Yet, only the data from the balloons with the highest average bursting point (i.e. the "blue" balloons) was used to develop their primary dependent measure, as they presumed that this balloon type was likely to capture the greatest amount of individual variability in task performance. The present implementation was thus based only on their blue balloon type, which had an average bursting point of 64 pumps. However, the second difference from the original task was that this average bursting point was lowered to 37.5 for all 30 balloons to accommodate time for the other tasks of the experiment, while still capturing significant individual variability in task performance.

During this portion of the experiment, participants were repeatedly presented with an uninflated balloon, which they were instructed to inflate by repeatedly pressing the right arrow on the keyboard. The balloon stimuli was an image of a blue balloon, next to which was displayed the total amount of points earned as well as the amount won from the previous balloon. After each inflation (i.e. key press), an inflation sound effect was produced, the balloon image grew in size, and 50 points were added to a temporary bank. The content of this temporary bank was hidden from participants at this point; they were only told that the larger they inflated the balloon, the more points could be earned from it. The inflation continued until either a win or a loss event. The former occurred when a participant decided to stop inflating the balloon before it burst, and to collect the points associated with it by pressing the left arrow, which produced a cash register sound that accompanied a feedback display revealing the amount of points won from the temporary bank. The latter happened when a participant inflated the balloon past its break point, in which case the balloon image was replaced with one of an exploded balloon, a "pop" sound was produced, and no points were added to the total. The visual feedback indicating win or loss remained on the screen for 2 seconds, and was then followed by a 1-second fixation cross which preceded the appearance of a new uninflated balloon. The task ended once participants had gone through 30 balloons.

The bursting point of each balloon (i.e. the number of inflations/pumps that will pop a specific balloon) was determined by randomly selecting an integer between 1 and 75 for every balloon, and using it as its bursting point. This algorithm resulted in a 1/75 theoretical probability of a balloon bursting after the first inflation. If a balloon did not explode after the first pump, its probability to burst after the second one became 1/74; 1/73 after the third one, and so on until the 75th pump, after which the probability of explosion was 1/1 (100%). As previously mentioned, this algorithm also resulted in an average bursting point of 37.5 pumps.

Importantly, participants were given no detailed information regarding the probability of a balloon exploding. All they were told was that, at some point, each balloon would explode, and that it could occur as early as the first pump all the way to the point at which the balloon scaled to the entire screen. In addition, participants first went through 3 practice trials to ascertain a good understanding of the task. Those included both win and loss events, which were forced by manually setting the bursting points of the practice balloons.

As for the risk preference index derived from the BART, the average number of "adjusted pumps" was used, as originally proposed by (C. W. Lejuez et al., 2002). It refers to the average number of pumps across all balloons that did not burst. Numerous studies have shown that this number correlates with various other measures of risk preference (Giustiniani et al., 2019; C. W. Lejuez et al., 2002, 2003).

Both the IGT and the BART were implemented in E-Prime 3.0.3.60 (Psychology Software Tools Inc., Pittsburgh, PA), and were displayed on the center screen. After these tasks, the mouse and keyboard were replaced with the racing wheel.

2.3.5 Experimental tasks - Driving simulation

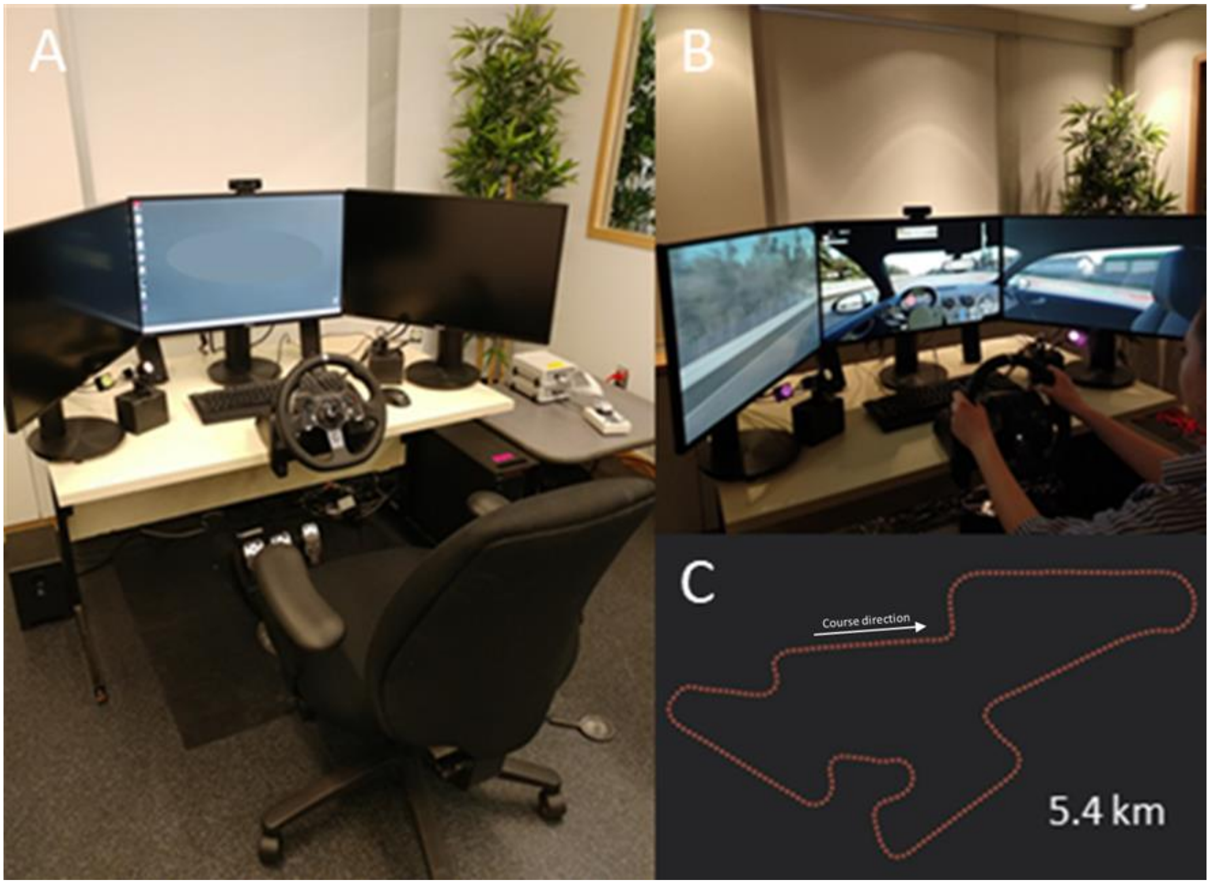

Figure 3. A. Apparatus used (details below). **B.** Project Cars 2 as simulation software, along with a third-party telemetry application (not shown). **C.** Race track: Brno Circuit.

The driving task consisted in completing five uninterrupted laps around a virtual race track, without any other cars present. At the end of each lap, an objective for the upcoming lap was verbally assigned as participants passed the finish line. For the first lap, the objective assigned simply consisted in getting accustomed to the driving of the car. Data from this lap was thus not considered in analysis. The objective associated with the second lap was to set a time, which served as a reference for the subsequent objective. For the third lap, we asked participants to try and beat their time by at least 10 seconds. Likewise, the objective associated with the fourth lap consisted in beating their previous time (from lap 3) by at least 10 seconds. Finally, for the fifth lap, the objective assigned was to beat the previous time (from lap 4) by at least 5 seconds, while not going off track more than 5 times. As mentioned above, these objectives were designed solely for the purpose of motivating risky driving behavior by encouraging fast driving; success in reaching the objectives was thus not measured.

The driving task was run using Project Cars 2 (Slightly Mad Studios Ltd., London, UK)—a highly realistic simulator often applied to professional training scenarios as well as scientific research. Ran on a Windows PC, this software allowed for the parallel use of a third-party application (pCARS Profiler by Tom Shane) that continuously recorded 173 measures of driving behavior (e.g. speed, lateral acceleration, steering), from which 4 were selected for the secondary analysis described below.

The track around which the task revolved was the Brno Circuit, a 5.4 km-long motorsport race track paved with asphalt. It was selected for its numerous pronounced curves as well as long straight segments, which allowed for a clear distinction between the two types of track segments. Such a clear distinction was necessary for the analysis of brain activity specifically related to decision making under risk while driving (see section 2.3.8). As for the car used in the driving task, the Audi A1 quattro was the one driven by all participants. Being the least powerful available in the game, this vehicle most closely simulated the driving of a regular car, as opposed to most other cars available which were designed for racing, and are thus much more difficult to handle.

During the whole experiment, participants sat on a fully adjustable stationary chair in front of three 27-inch LED monitors producing a total resolution of 5760x1080 pixels. The center screen stood approximately 90 cm away from their eyes, and the lateral ones were positioned at a 55° angle, providing a 120° field of view. Participants were equipped with a keyboard, a mouse and a Logitech (Logitech International S.A., Lausanne, Switzerland) G920 racing wheel with force-feedback steering and realistic pedal feel. Before the driving task, individual adjustments were routinely made to the pedal unit and the chair to ensure that all participants sat in a comfortable driving position. Throughout the experiment, sound was outputted at a comfortable volume through a set of Logitech X-240 stereo speakers and their dedicated subwoofer.

The aforementioned analysis of car telemetry focused on 4 continuous variables employed to operationalize risky driving behavior: longitudinal speed (km/h), steering (a positive number proportional to the amount of steering in any direction), lateral acceleration (g) and engine speed (rpm). These measures are very similar to those used by insurance companies that employ telematics to adapt their services (Tselentis et al., 2017). Under the fast driving conditions that were promoted, all 4 of these variables were assumed to be positively associated with an increased risk of accident. That is especially the case in curved sections of the track, where these variables vary greatly depending on the level of risk incurred throughout such sections. For this reason, only the telemetric data from curved segments (see Figure 4 below) was included in the analysis described in sections 2.3.9 and 2.3.10.

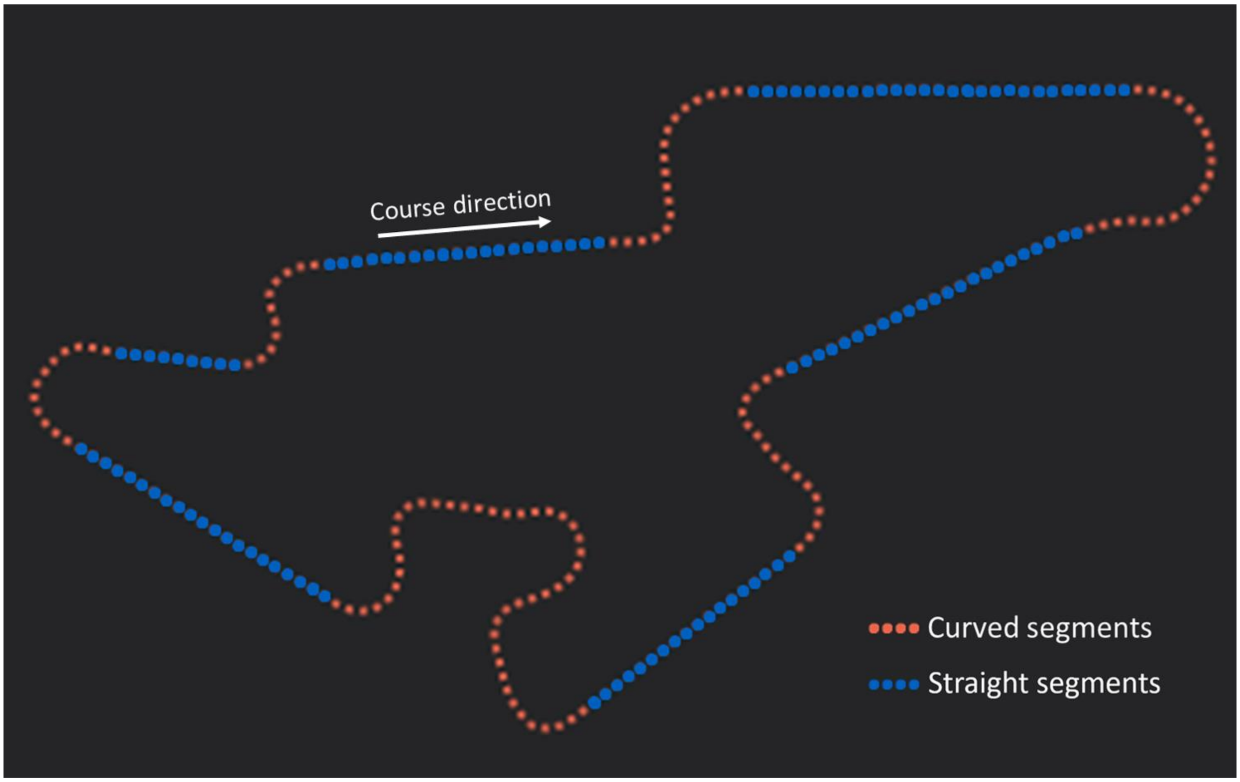

Figure 4. Track breakdown in terms of straight and curved segments.

2.3.6 Psychometry - Domain-Specific Risk-Taking scale

The DOSPERT scale was designed to assess risk preference in five domains of everyday life: the financial, health/safety, recreational, ethical and social domains of risky decisions. In this scale, participants used an iPad to rate—on a 7-point Likert scale—the likelihood that they would engage in domain-specific risky activities. The global risk preference score was produced by averaging all responses, while domain-specific scores were produced by averaging responses associated with each domain.

2.3.7 Experimental procedure

In the first half of the experiment, participants were asked to complete the two computerized risk tasks (IGT & BART) in an order that was counterbalanced per participant. These tasks involved simple economic decisions in a synthetic context, and served the purpose of objectively quantifying risk preference through behavior. The second half of the experiment consisted in the simulated driving task designed to elicit decisions under risk in a more naturalistic context. Before the driving task, participants watched a 5-minute video of nature scenery that was intended to return participants to a calm state of physiological arousal. After the driving task, the experiment ended with two questionnaires filled out on a tablet. The first one consisted in a very short sociodemographic assessment, which was followed by the 30-item French version of the Domain-Specific Risk-Taking scale from (Blais & Weber, 2006).

The study's online description for recruitment indicated only a $40 gift card as compensation; the real amount was—purposefully—only revealed halfway through the experiment. At the very beginning of the driving task, participants were informed that, based on their success in reaching task objectives (see section 2.3.5), they could actually earn an additional compensation of up to $10 in value. This alleged bonus ultimately served to encourage participants to drive faster, which, considering the track's pronounced curves, was assumed to create conditions conducive to significant levels of decision making under risk in certain parts of the track, which are specified in the next section. The full bonus amount was given to all participants.

2.3.8 Neurophysiological measures

Brain activity was recorded at 1000 Hz using a 64-channel EEG (Brain Products GmbH, Gilching, Germany) with a sensor layout based on the International 10-20 system. During the EEG setup, a CapTrak (Brain Products GmbH, Gilching, Germany) scanner was employed to digitize electrode positions, thereby permitting localization of the brain activity on the cortical surface.

EEG signals were pre-processed and analyzed in Brainstorm (Tadel et al. 2011), which is documented and freely available for download online under the GNU general public license. The application was run in MATLAB R2018a version 9.4.0.813654. Components of physiological artifacts and periodic noise were isolated and removed using independent component analysis. The segments with remaining artifacts larger than ± 100 μV were manually rejected. Signals were then downsampled to 500 Hz from 1000 Hz, after which a band-pass filter was applied from 5 Hz to 30 Hz.

Following pre-processing, the driving task EEG time series was then synchronized with the telemetry data through markers that were manually added to the EEG recording at the beginning of each lap during data collection. Next, the driving task EEG time series from laps 2 through 5 were marked at one-second intervals, and markers were manually labeled—through a visual inspection of the car's position in the telemetry software—based on whether the car was located on a "straight" or a "curved" segment of the track during the one second following the marker (see Figure 4 for the specific distinction on the track).

The rationale behind this distinction stems from two assumptions that were made regarding the level of risk encountered in parts of these track segments. The first one is that, when driving through the beginning of straight segments (far from an upcoming curve), the level of risk is at its lowest as the driver needs to do nothing more than accelerate and keep the steering wheel straight. Therefore, there should not be any important motor decision to be made in order to drive as fast as possible through the beginning of straight segments. Conversely, the second assumption is that, when driving through the very end of straight segments as well as the beginning of curved segments, the level of risk is at its highest. This is because numerous motor decisions related to braking/acceleration and steering are required in a short amount of time, and if not executed well will adversely affect driving performance (e.g. going off road). In the later part of a curve, risk is still at play, but to a much lesser extent as most decisions necessary to successfully navigate the curve have arguably already been made.

Based on the above logic, we decided to target brain activity during driving segments at the very end of straights and beginning of curves where the greatest amount of decision making under risk (DMUR) occurs (hereafter high DMUR segments). Manual inspection of driving telemetry revealed that a window of five seconds was sufficient to capture all high DMUR segments in all participants. Thus, the first five one-second markers within these segments were selected for epoching and further analysis. To capture brain activity related to DMUR and exclude brain activity related to driving in general, we decided that brain activity during high DMUR segments should be normalized against brain activity during driving segments at the beginning of straights where the lowest amount of DMUR occurs (hereafter low DMUR segments). Manual inspection of driving telemetry revealed that a window of three seconds was sufficient to capture all low DMUR segments in all participants. Thus, the first three one-second markers within these segments were selected for epoching and further analysis.

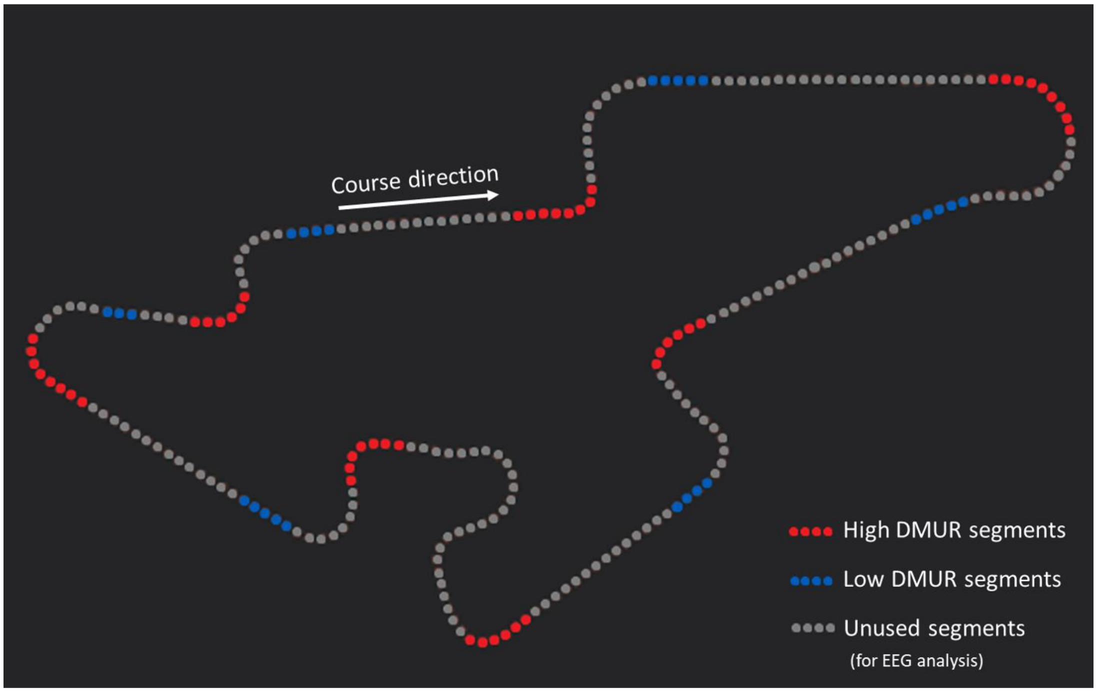

Figure 5. Track breakdown* for EEG analysis. *The actual length of each segment varies slightly for any given lap since it is determined by speed (e.g. lower speed leads to a shorter segment of the track).

The pre-processed EEG signals were epoched around high and low DMUR markers using a window of -200 to +1700 ms with respect to markers. Next, an EEG-appropriate forward model was estimated based on the digitized electrode positions using OpenMEEG. Then, minimum norm estimation was used to calculate cortical currents without dipole orientation constraints for all epochs. Source-level brain activity in each epoch was then time-frequency (TF) decomposed in the theta (5-7 Hz), alpha (8-12 Hz) and beta (15-29 Hz) frequency bands using Morlet wavelets (with a central frequency of 1 Hz and a time resolution of 3 seconds). Next, source-level theta, alpha and beta activities were averaged separately across high DMUR and low DMUR epochs in each participant, and then averaged over time from 0-1 s. Mean high DMUR cortical activity was normalized using mean low DMUR cortical activity for each frequency band according to the following equation:

$$x\_std = (x - \mu) / \mu * 100$$

where x_std is normalized activity, x is mean high DMUR cortical activity, and μ is mean low DMUR cortical activity.

Finally, the cortex was divided into 62 brain areas according to the Mindboggle brain atlas, which is included in Brainstorm software. Normalized brain activity from each participant from each brain area in each frequency band was then extracted for statistical analysis.

2.3.9 Telemetry processing

For each of the four variables selected (longitudinal speed, steering, lateral acceleration and engine speed), the time series associated with all curved segments of laps 2 through 5 were averaged both across the segments themselves and over time, producing 4 values per participant (one per telemetry variable).

2.3.10 Statistical analyses

For analysis purposes, the IGT was divided into 4 blocks: block 1 (trials 0-20), block 2 (trials 21-40), block 3 (trials 41-60) and block 4 (trials 61-75). To assess the progression of decision patterns of participants over the course of this task, a 1-way repeated measures ANOVA was first performed for each deck to assess the effect of block on the selection of cards from each deck. These ANOVA comprised block as a 4-level within-subjects factor, and the proportion of selection from the deck in question as the dependent variable and repeated measure.

Next, to assess whether learning of the payoff contingencies led to more advantageous choices later in the task, the effect of block on the proportion of advantageous selections was examined. A 1-way repeated measures ANOVA was thus performed again with block as a 4-level within-subjects factor, and the proportion of advantageous selections as the dependent variable and repeated measure.

For the driving simulation, the relationships between risk preference (from the IGT, BART and DOSPERT) and normalized high DMUR brain activity were assessed through repeated measures multivariate linear regression separately for each frequency band and for each risk preference assessment task, with brain activity in each of the 62 brain areas as dependent variable and repeated measure. A total of 24 models were thus run for this portion of analysis, since 3 frequency bands were considered and 8 measures of risk preference were analyzed: the IGT index, the BART index, and the 6 DOSPERT scores (one for each of the 5 risk domains and the global score). In cases where a significant interaction between brain area and risk preference was observed, simple main effects testing was performed to assess the relationship within each brain area separately.

Meanwhile, the relationships between risk preference measures and driving behavior were also assessed through repeated measures multivariate linear regression separately for each measure of risk preference, with mean telemetric measurement for each of the 4 variables as dependent variable and repeated measure. A total of 8 models were thus run for this portion of analysis (one per risk preference measure). When a significant interaction between telemetry measure and risk preference was observed, simple main effects testing was performed to assess the relationship for each telemetry variable separately. All statistical analyses were performed using SPSS version 25 (IBM Corp., Armonk, NY). The threshold for significance was set at $p \leq 0.05$.

2.4 Results

2.4.1 Descriptive statistics - Iowa Gambling Task

The breakdown of deck selections for each block as well as for the whole task is shown in figures 6 and 7.

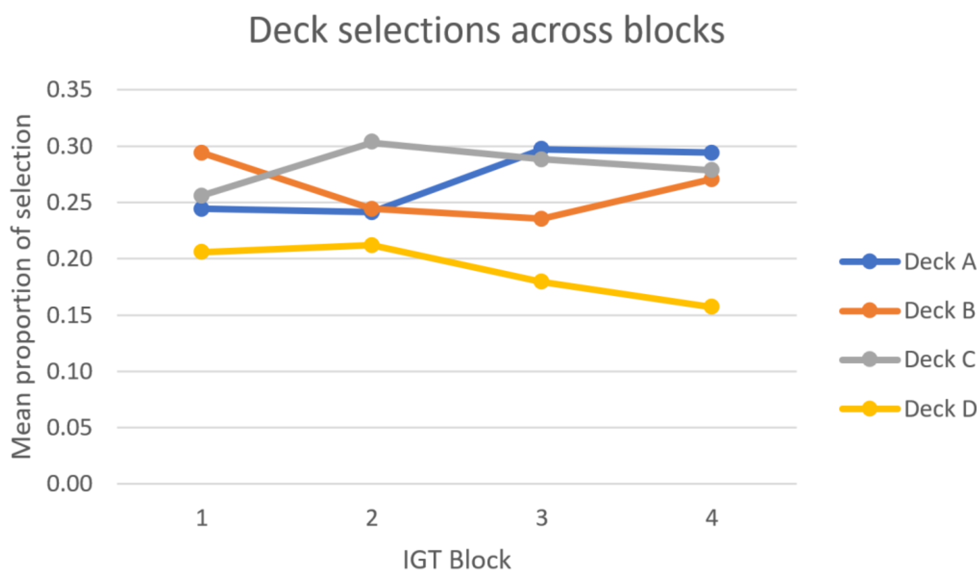

Figure 6. IGT deck selections across blocks

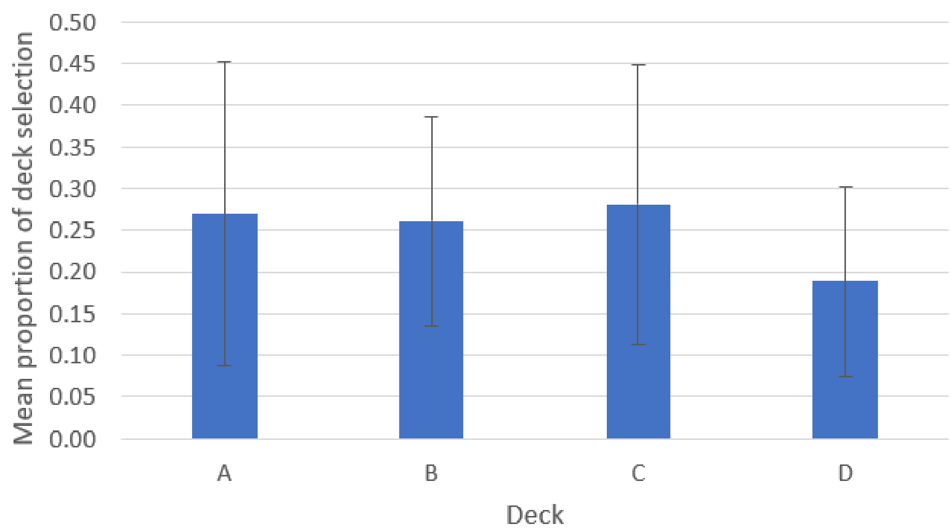

Figure 7. IGT deck selections over 75 trials. Error bars represent standard deviations.

The standard deviation bars in Figure 7 indicate a very high variability in deck selections among participants, suggesting a high variability in patterns of decision making or strategies employed.

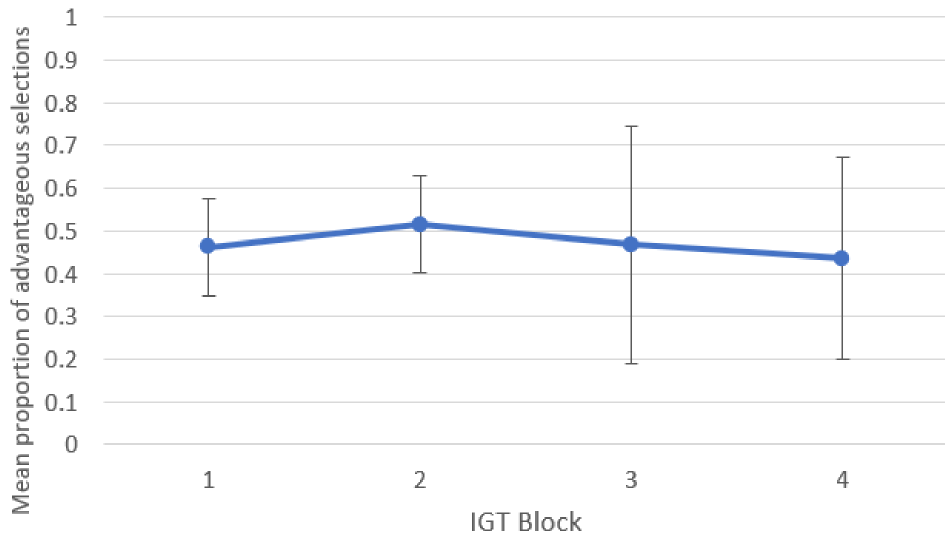

Figure 8. Proportion of advantageous IGT selections across blocks. Error bars represent standard deviations.

The proportion of advantageous selections for each block is depicted in Figure 8. This chart indicates two notable trends: on average, participants exhibited a pattern of decisions that did not progress towards advantageous choices over the course of the task, and the high variability observed previously is more pronounced in the last two blocks.

The post-learning performance index (from trials 41-75) across all participants presented an average of -3.24 and a standard deviation of 16.42. The latter indicates that participants did exhibit a wide range of performance outcomes in the relevant part of the task, which suggests that there were important differences in decision strategies and/or experience-based learning across participants. While potentially useful for our purposes, such a large range of performance outcomes is unusual in healthy populations. The potential reasons underlying this discrepancy are expanded upon in section 2.5.1.

2.4.2 *Descriptive statistics - Balloon Analogue Risk Task*

Likewise, participants exhibited a wide range of performance outcomes in the BART; behavioral risk-taking measures were characterized by a mean of 27.4 adjusted pumps and a standard deviation of 10.5. The average number of adjusted pumps observed is in line (less than one standard deviation away) with what was observed in previous studies (C. W. Lejuez et al., 2003; Xu et al., 2013)**.**

2.4.3 *Descriptive statistics - Driving behavior*

Table 3. Mean telemetric measurements in curved segments of laps 2-5

Telemetry variable	Mean measurement across curved segments of laps 2-5	S.D.
Longitudinal speed (km/h)	98.22	7.59
Steering	3.47	1.84
Lateral acceleration (*g*)	-0.10	0.21
Engine speed (rpm)	5179.46	85.98

The mean telemetric measurements and the standard deviations shown above indicate significant variability across participants in terms of steering and lateral acceleration during curves. Considering the aforementioned assumption of a link between these variables and risky driving under the fast driving conditions promoted, this data suggests that participants have exhibited a relatively wide range of riskiness during the relevant portions of the driving simulation.

2.4.4 Descriptive statistics - Domain-Specific Risk-Taking scale

Table 4. Mean DOSPERT scores across risk dimensions

DOSPERT score (7-point scale)	Overall (n = 18)	
Risk dimension	**Mean**	**S.D.**
Global	4.04	0.49
Ethical	2.58	0.86
Financial	3.30	1.23
Health/Safety	3.57	0.75
Recreational	5.04	0.89
Social	5.70	0.82

The mean DOSPERT scores shown above are in line with what should be expected from a healthy population; the mean score for each dimension is fairly close (less than a standard deviation away) to what was observed in previous studies (Blais & Weber, 2006; Hu & Xie, 2012).

2.4.5 Performance - Iowa Gambling Task

No main effect of block was found for the selection proportions of decks A($F_{(3,48)} = 0.508, p = 0.679$), B($F_{(3,48)} = 1.332, p = 0.275$), C($F_{(3,48)} = 0.318, p = 0.812$), and D($F_{(3,48)} = 0.836, p = 0.481$). Decision patterns of participants thus did not change significantly over the course of the task. Similarly, regarding the proportion of advantageous selections, the repeated measures ANOVA revealed no effect of block on this proportion ($F_{(3,48)} = 0.634, p = 0.597$). Therefore, on average, participants did not exhibit a pattern of decisions that progressed towards advantageous choices over the course of the task.

2.4.6 Driving brain activity & IGT performance

In the regression models pertaining to the IGT index of risk preference, brain area was found to have a significant main effect on normalized high-DMUR brain activity for all frequency bands tested: theta ($F_{(61,915)} = 19.430, p < 0.000$), alpha ($F_{(61,915)} = 7.324, p < 0.000$) and beta ($F_{(61,915)} = 3.541, p < 0.000$). In addition, the IGT index did not have a significant effect on normalized high-DMUR brain activity for all frequency bands tested: theta ($F_{(1,15)} = 0.330, p = 0.574$), alpha ($F_{(1,15)} = 0.023, p = 0.881$) and beta ($F_{(1,15)} = 0.001, p = 0.978$). More importantly, no significant interaction was found between brain area and the IGT index of risk preference, regardless of frequency band: theta ($F_{(61,915)} = 1.088, p = 0.304$), alpha ($F_{(61,915)} = 0.480, p = 1.000$) and beta ($F_{(61,915)} = 0.973, p = 0.536$). Therefore, the relationship between the IGT index of risk preference and high-DMUR brain activity did not differ according to brain area.

2.4.7 Driving brain activity & BART performance

In the models pertaining to the BART index of risk preference, brain area was found to have a significant main effect on normalized high-DMUR brain activity for the theta ($F_{(61,915)} = 2.878, p < 0.000$) and alpha ($F_{(61,915)} = 1.538, p = 0.006$) bands. This effect did not reach significance for the beta band ($F_{(61,915)} = 0.756, p = 0.916$). In addition, the BART index did not have a significant effect on normalized high-DMUR brain activity for all frequency bands tested: theta ($F_{(1,15)} < 0.001, p = 0.996$), alpha ($F_{(1,15)} = 0.079, p = 0.783$) and beta ($F_{(1,15)} = 0.270, p = 0.611$). As with the IGT, no significant interaction was found between brain areas and the BART index of risk preference, regardless of frequency band: theta ($F_{(61,915)} = 1.088, p = 0.304$), alpha ($F_{(61,915)} = 1.039, p = 0.398$) and beta ($F_{(61,915)} = 0.393, p = 1.000$). Therefore, the relationship between BART performance and driving brain activity did not differ according to brain area.

2.4.8 Driving brain activity & DOSPERT scores

In the models pertaining to the global DOSPERT score, brain area was found to have a significant main effect on normalized high-DMUR brain activity in the beta band only ($F_{(61,915)} = 1.812, p < 0.000$). This effect did not reach significance for the theta ($F_{(61,915)} = 1.019, p = 0.438$) and alpha ($F_{(61,915)} = 1.031, p = 0.414$) bands. In addition, the global score did not have a significant effect on normalized high-DMUR brain activity for all frequency bands tested: theta ($F_{(1,15)} = 0.619, p = 0.444$), alpha ($F_{(1,15)} = 0.526, p = 0.480$) and beta ($F_{(1,15)} = 0.128, p = 0.725$). More importantly, a significant interaction was found between brain areas and the global DOSPERT score for the alpha ($F_{(61,915)} = 1.336, p = 0.047$) and beta ($F_{(61,915)} = 1.969, p = 0.000$) frequency bands. Yet, within those bands, parameter estimates revealed no significant relationship between brain activity in any specific area and the global DOSPERT score (p > 0.05). The same interaction did not reach significance for the theta frequency band ($F_{(61,915)} = 1.185, p = 0.163$). Therefore, while the relationship between the DOSPERT scale as a whole and brain activity related to risky decision making during the driving task did differ according to brain area for the alpha and beta bands, this relationship was not found to be significant in any brain area. As for the theta frequency band, this relationship did not significantly differ according to brain area. However, individual dimensions of the DOSPERT questionnaire yielded disparate results.

In the models pertaining to the ethical dimension of risk, brain area was found to have a significant main effect on high-DMUR brain activity in the theta frequency band ($F_{(61,915)} = 2.458, p < 0.000$). This effect did not reach significance in the alpha ($F_{(61,915)} = 1.026, p = 0.423$) and beta ($F_{(61,915)} = 1.049, p = 0.377$) bands. In addition, the ethical score did not have a significant effect on normalized high-DMUR brain activity for all frequency bands tested: theta ($F_{(1,15)} = 0.080, p = 0.781$), alpha ($F_{(1,15)} < 0.001, p = 0.990$) and beta ($F_{(1,15)} = 0.019, p = 0.892$). More importantly, the interaction between brain areas and the ethical risk score was statistically significant for the theta band ($F_{(61,915)} = 1.667, p = 0.001$). However, parameter estimates revealed no significant relationship between theta brain activity in any specific area and the ethical DOSPERT score (p > 0.05). The same interaction did not reach significance for the alpha

($F_{(61,915)} = 1.090, p = 0.302$) and beta ($F_{(61,915)} = 0.698, p = 0.962$) bands. Therefore, while the relationship between the ethical DOSPERT score and brain activity related to risky decision making during the driving task did differ according to brain area for the theta frequency band, this relationship was not found to be significant in any brain area. As for the alpha and beta bands, this relationship did not significantly differ according to brain area.

In the models pertaining to the financial dimension of risk, brain area was found to have a significant main effect on high-DMUR brain activity in the theta ($F_{(61,915)} = 2.920, p < 0.000$) and alpha ($F_{(61,915)} = 1.624, p = 0.002$) frequency bands. This effect did not reach significance in the beta band ($F_{(61,915)} = 1.101, p = 0.283$). In addition, the financial score did not have a significant effect on normalized high-DMUR brain activity for all frequency bands tested: theta ($F_{(1,15)} = 0.836, p = 0.375$), alpha ($F_{(1,15)} = 0.433, p = 0.520$) and beta ($F_{(1,15)} = 0.013, p = 0.912$). More importantly, the interaction between brain areas and the financial risk score did not reach statistical significance, regardless of frequency band: theta ($F_{(61,915)} = 0.814, p = 0.844$), alpha ($F_{(61,915)} = 0.569, p = 0.997$) and beta ($F_{(61,915)} = 0.678, p = 0.972$). Therefore, the relationship between the financial DOSPERT score and brain activity related to risky decision making during the driving task did not differ according to brain area.

In the models pertaining to the health/safety dimension of risk, brain area was found to have a significant main effect on high-DMUR brain activity in all frequency bands tested: theta ($F_{(61,915)} = 0.929, p = 0.631$), alpha ($F_{(61,915)} = 0.309, p = 1.000$) and beta ($F_{(61,915)} = 0.188, p = 1.000$). In addition, the health/safety score did not have a significant effect on normalized high-DMUR brain activity for all frequency bands tested: theta ($F_{(1,15)} = 0.015, p = 0.903$), alpha ($F_{(1,15)} = 0.252, p = 0.623$) and beta ($F_{(1,15)} = 0.044, p = 0.837$). More importantly, the interaction between brain areas and the health/safety risk score was statistically significant for the theta band ($F_{(61,915)} = 1.348, p = 0.043$). However, parameter estimates revealed no significant relationship between theta brain activity in any specific area and the health/safety DOSPERT score (p > 0.05). The same interaction did not reach significance for the alpha ($F_{(61,915)} = 0.670, p = 0.975$) and beta ($F_{(61,915)} = 0.177, p = 1.000$) bands. Therefore, while the relationship between the health/safety DOSPERT score and brain activity related to risky decision making during the driving task did differ according to brain area for the theta frequency band, this relationship was not found to be significant in any brain area. As for the alpha and beta bands, this relationship did not significantly differ according to brain area.

In the models pertaining to the recreational dimension of risk, brain area was found to have a significant main effect on high-DMUR brain activity in all frequency bands tested: theta ($F_{(61,915)} = 1.670, p = 0.001$), alpha ($F_{(61,915)} = 2.492, p < 0.000$) and beta ($F_{(61,915)} = 1.405, p = 0.025$). In addition, the recreational score did not have a significant effect on normalized high-DMUR brain activity for all frequency bands tested: theta ($F_{(1,15)} = 2.312, p = 0.149$), alpha ($F_{(1,15)} = 0.252, p = 0.623$) and beta ($F_{(1,15)} = 0.857, p = 0.369$). More importantly, the interaction between brain areas and the recreational risk score was statistically significant for all bands: theta ($F_{(61,915)} = 1.416, p = 0.022$), alpha ($F_{(61,915)} = 3.491, p < 0.000$) and beta ($F_{(61,915)} = 2.021, p < 0.000$). Parameter estimates indicated significant relationships between brain activity in numerous areas and the recreational risk score. The significant relationships are listed in Table 5 below. The recreational DOSPERT score was thus significantly associated with brain activity related to risky decision making during the driving task.

Table 5. *Significant relationships between normalized high-DMUR brain activity in specific brain areas and frequency bands, and the mean recreational DOSPERT score*

Dependent variable (brain area)	Frequency band	Independent variable	Beta estimate	Standard error	t	Sig.
Right fusiform	Theta (5-7 Hz)	Mean recreational risk score	11.775	4.943	2.382	0.031
Left lateral occipital			11.516	4.535	2.540	0.023
Left lingual			14.704	4.664	3.153	0.007
Right lingual			10.111	4.414	2.291	0.037
Left pericalcarine			12.018	3.971	3.027	0.008
Right fusiform	Alpha (8-12 Hz)		23.249	10.430	2.229	0.042
Right inferior parietal			16.944	4.899	3.459	0.004
Right inferior temporal			20.579	9.404	2.188	0.045
Left lateral occipital			16.833	6.344	2.654	0.018

Right lateral occipital		Mean recreational risk score	13.362	4.722	2.829	0.013
Left lingual			21.192	8.055	2.631	0.019
Right lingual			18.840	7.205	2.615	0.020
Right middle temporal			16.811	7.041	2.388	0.031
Left pericalcarine			18.834	5.968	3.156	0.007
Right pericalcarine			14.313	4.968	2.881	0.011
Left superior parietal			7.987	3.504	2.280	0.038
Right superior temporal			13.414	6.151	2.181	0.046
Right supramarginal			14.181	5.505	2.576	0.021
Right transverse temporal			12.675	5.761	2.200	0.044
Left cuneus	Beta (15-29 Hz)		10.2902	4.2741	2.4075	0.0294
Right cuneus			9.8478	4.3242	2.2774	0.0378
Right inferiorparietal			17.2043	4.7968	3.5866	0.0027
Right lateral occipital			14.9975	5.5155	2.7191	0.0158
Right lingual			15.6437	6.6637	2.3476	0.0330
Left pericalcarine			20.6456	8.6223	2.3944	0.0302
Right pericalcarine			15.6788	5.9748	2.6241	0.0192
Right superior parietal			8.6302	3.9002	2.2128	0.0428

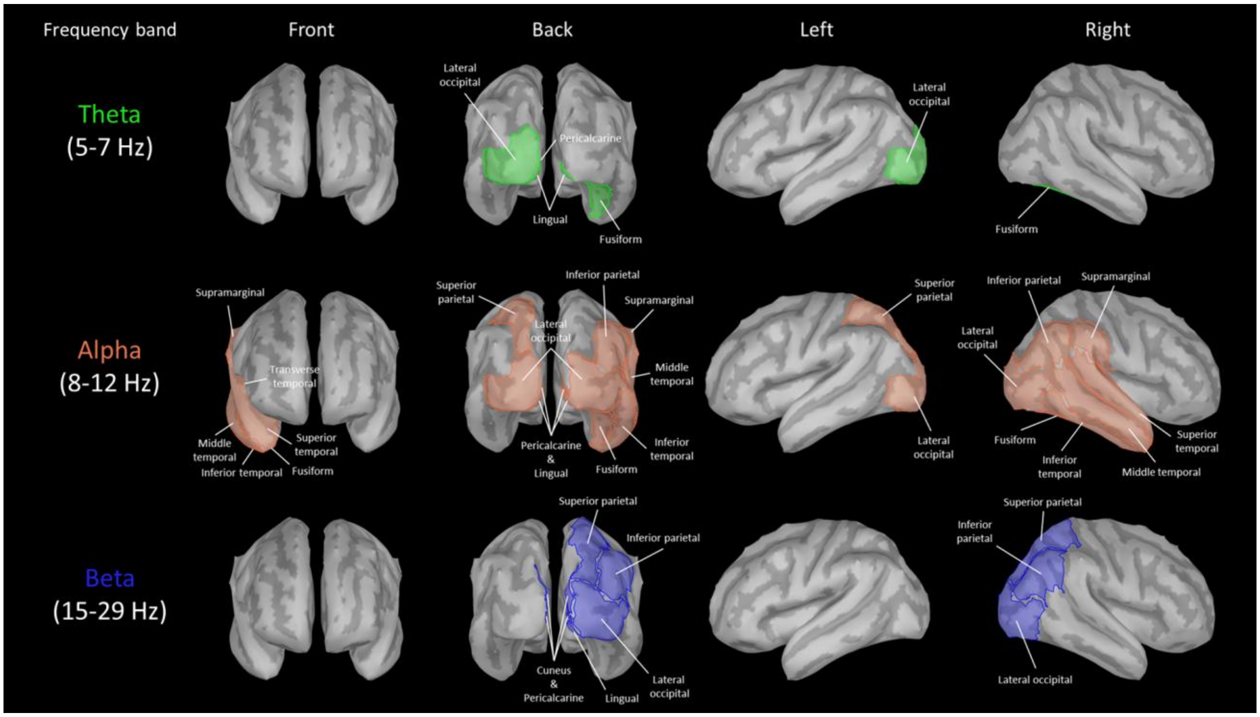

Figure 9. Anatomical representation of the brain areas listed in Table 5.

In the models pertaining to the social dimension of risk, brain area was found to have a significant main effect on high-DMUR brain activity in the beta frequency band ($F_{(61,915)} = 2.242, p < 0.000$). This effect did not reach significance in the theta ($F_{(61,915)} = 0.959, p = 0.566$) and alpha ($F_{(61,915)} = 0.928, p = 0.633$) bands. In addition, the social score did not have a significant effect on normalized high-DMUR brain activity for all frequency bands tested: theta ($F_{(1,15)} = 0.014, p = 0.906$), alpha ($F_{(1,15)} = 0.484, p = 0.497$) and beta ($F_{(1,15)} = 3.878, p = 0.068$). More importantly, the interaction between brain areas and the social risk score was statistically significant for the beta band ($F_{(61,915)} = 1.667, p = 0.001$). Parameter estimates indicated significant relationships between brain activity in numerous areas and the social risk score. The significant relationships are listed in Table 6 below. The same interaction did not reach significance for the theta ($F_{(61,915)} = 0.522, p = 0.999$) and alpha ($F_{(61,915)} = 0.718, p = 0.948$) bands. The social DOSPERT score was thus significantly associated with beta brain activity related to risky decision making during the driving task. However, the relationship between the social DOSPERT score and brain activity related to risky decision making during the driving task did not differ according to brain area for the theta and alpha frequency bands.

Table 6. Significant relationships between normalized high-DMUR beta brain activity in specific brain areas, and the mean social DOSPERT score.

Dependent variable (brain area)	**Frequency band**	**Independent variable**	**Beta estimate**	**Standard error**	**t**	**Sig.**
Left caudal middle frontal	Beta (15-29 Hz)	Mean social risk score	-17.607	6.622	-2.659	0.018
Right caudal middle frontal			-17.290	6.884	-2.511	0.024
Left insula			-18.801	6.269	-2.999	0.009
Left pars opercularis			-30.928	9.420	-3.283	0.005
Right pars opercularis			-23.026	7.872	-2.925	0.010
Left pars orbitalis			-23.744	7.418	-3.201	0.006
Left pars triangularis			-28.550	8.814	-3.239	0.006
Right pars triangularis			-16.092	7.004	-2.298	0.036
Left post-central			-15.398	5.181	-2.972	0.009
Right post-central			-18.681	8.507	-2.196	0.044
Left pre-central			-18.128	5.938	-3.053	0.008
Right pre-central			-22.818	8.666	-2.633	0.019
Left rostral middle frontal			-17.322	6.443	-2.688	0.017
Right rostral middle frontal			-13.956	6.452	-2.163	0.047
Left superior temporal			-14.614	6.680	-2.188	0.045
Left supramarginal			-21.050	7.095	-2.967	0.010
Left transverse temporal			-14.918	6.420	-2.324	0.035
Right transverse temporal			-18.197	8.021	-2.269	0.038

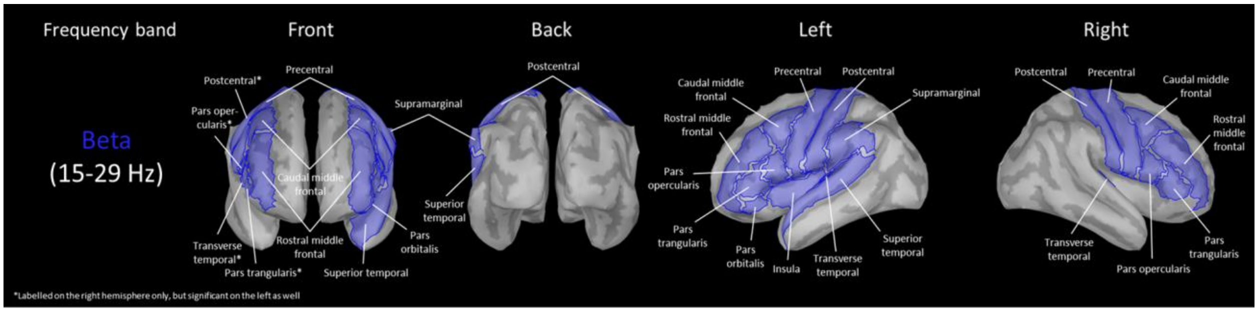

Figure 10. Anatomical representation of the brain areas listed in Table 6.

2.4.9 Driving behavior (telemetry) & IGT performance

In the model pertaining to the IGT index of risk preference, telemetry variable was found to have a significant main effect on the values of the telemetric measurements considered ($F_{(3,45)} = 58935.282, p < 0.000$), while the IGT index did not have a significant effect on those values ($F_{(1,15)} = 1.056, p = 0.320$). In addition, no significant interaction was found between telemetry variables and the IGT index of risk preference ($F_{(3,45)} = 1.251, p = 0.303$). Therefore, the relationship between risk preference exhibited in the IGT and driving behavior in risky portions of the driving task did not differ according to the telemetric measurement considered.

2.4.10 Driving behavior (telemetry) & BART performance

In the model pertaining to the BART index of risk preference, telemetry variable was found to have a significant main effect on the values of the telemetric measurements considered ($F_{(3,45)} = 56374.116, p < 0.000$), while the BART index did not have a significant effect on those values ($F_{(1,15)} = 0.310, p = 0.586$). In addition, no significant interaction was found between telemetry variables and the BART index of risk preference ($F_{(3,45)} = 0.539, p = 0.658$). Therefore, the relationship between risk preference exhibited in the BART and driving behavior in risky portions of the driving task did not differ according to the telemetric measurement considered.

2.4.11 Driving behavior (telemetry) & DOSPERT scores

In the model pertaining to the global DOSPERT score, telemetry variable was found to have a significant main effect on the values of the telemetric measurements considered ($F_{(3,45)} = 794.577, p < 0.000$). The global score also had a significant effect on those values ($F_{(1,15)} =$

$5.392, p = 0.035$). A significant interaction was found between telemetry variable and the global DOSPERT score ($F_{(3,45)} = 3.974, p = 0.014$). Parameter estimates indicated a significant positive relationship between the global score and 2 telemetry variables: speed in curves ($B = 12.847, t = 4.709, p < 0.000$) and steering in curves ($B = 2.305, t = 2.696, p = 0.017$). In other words, higher risk preference in everyday life—as measured by the DOSPERT questionnaire as a whole—was associated with driving behavior presumed as more risky, i.e. higher speed as well as more steering in the curves of the driving simulation (on average).

In the model pertaining to the ethical DOSPERT score, telemetry variable was found to have a significant main effect on the values of the telemetric measurements considered ($F_{(3,45)} = 7154.603, p < 0.000$). The ethical score also had a significant effect on those values ($F_{(1,15)} = 5.076, p = 0.040$). A significant interaction was found between telemetry variable and the ethical risk score ($F_{(3,45)} = 5.168, p = 0.004$). Parameter estimates indicated a significant positive relationship between the ethical risk score and engine speed in curves ($B = 50.458, t = 2.276, p = 0.038$). In other words, higher risk preference in the ethical domain of everyday life—as measured by a subscale of the DOSPERT questionnaire—was associated with an increased (on average) engine speed in curves of the driving simulation, which was also presumed as evidence of taking more risks while driving.

In the model pertaining to the financial DOSPERT score, telemetry variable was found to have a significant main effect on the values of the telemetric measurements considered ($F_{(3,45)} = 5425.568, p < 0.000$), while the financial score did not have a significant effect on those values ($F_{(1,15)} = 0.427, p = 0.523$). In addition, no significant interaction was found between telemetry variable and the financial risk score ($F_{(3,45)} = 0.163, p = 0.921$). Therefore, the relationship between the financial DOSPERT score and behavioral features of risky driving in the simulation did not differ according to the telemetric measurement considered.

In the model pertaining to the health/safety DOSPERT score, telemetry variable was found to have a significant main effect on the values of the telemetric measurements considered ($F_{(3,45)} = 2343.386, p < 0.000$), while the health/safety score did not have a significant effect on those values ($F_{(1,15)} = 0.861, p = 0.368$). In addition, no significant interaction was found between telemetry variable and the health/safety risk score ($F_{(3,45)} = 0.581, p = 0.631$). Therefore, the relationship between the health/safety DOSPERT score and behavioral features of risky driving in the simulation did not differ according to the telemetric measurement considered.

In the model pertaining to the recreational DOSPERT score, telemetry variable was found to have a significant main effect on the values of the telemetric measurements considered ($F_{(3,45)} = 1691.418, p < 0.000$), while the recreational score did not have a significant effect on those values ($F_{(1,15)} = 2.542, p = 0.132$). In addition, no significant interaction was found between telemetry variable and the recreational risk score ($F_{(3,45)} = 2.191, p = 0.102$). Therefore, the relationship between the recreational DOSPERT score and behavioral features of risky driving in the simulation did not differ according to the telemetric measurement considered.

In the model pertaining to the social DOSPERT score, telemetry variable was found to have a significant main effect on the values of the telemetric measurements considered ($F_{(3,45)} = 1119.214, p < 0.000$), while the social score did not have a significant effect on those values ($F_{(1,15)} = 0.115, p = 0.740$). In addition, no significant interaction was found between telemetry variable and the social risk score ($F_{(3,45)} = 0.093, p = 0.964$). Therefore, the relationship between the social DOSPERT score and behavioral features of risky driving in the simulation did not differ according to the telemetric measurement considered.

2.5 Discussion

A better understanding of the psychological and neurophysiological factors associated with risky driving is essential for the development of experimental measures with predictive validity regarding this behavior. The goal of this study was to find such a measure—of the chosen psychological trait, i.e. risk preference—while using electroencephalography to investigate potential neurophysiological factors supporting any association found between a risk preference measure and risky driving behavior in a driving simulation.

In terms of behavioral results, the risk preference indices derived from the IGT and the BART were not associated with the measures of risky driving behavior from the driving simulation. However, the global DOSPERT score was associated with higher speed as well as more steering in the track's curves. The ethical score from the same scale was associated with higher engine speed in the curves. As for the neurophysiological data, significant associations were only found between two DOSPERT scores (social and recreational) and brain activity during the risky portions of the driving simulation. Therefore, no neurophysiological support was found for the associations observed between DOSPERT scores and risky driving behavior.

This research indicates that, despite a lack of neurophysiological evidence to support it, the DOSPERT scale as a whole (i.e. the global score) appears to have predictive validity with respect to risky driving behavior in a simulator, while the standardized behavioral risk-taking tasks that were considered (the IGT and the BART) do not. These findings contribute to the assessment of drivers' propensity for risk on the road (including distracted driving) by evaluating different risk preference measurement tools and their potential to act as predictors of risky driving. In addition, this work informs future research interested in either operationalizing risky driving behavior in a laboratory environment and/or studying brain activity associated with risky driving by attempting both using a simple driving task paradigm and an analysis method designed to isolate EEG signals specific to risky driving. In the rest of this section, each risk preference instrument is discussed, and the implications and limitations of this research are explored.

2.5.1 Iowa Gambling Task

Performance results from the IGT show a large range of decision outcomes—larger than what would theoretically be expected from a healthy population. The main reason for this variability is that 8 participants out of 18 made more selections from the disadvantageous decks than the advantageous ones, similarly to what was observed in patients with damage to the ventromedial prefrontal cortex (Bechara et al., 1994).

Poor IGT performance from healthy participants is not unheard of. In a meta-analysis, (Steingroever et al., 2013) concluded that the poor performance of many healthy participants seems to be the result of them having difficulty figuring out that deck B is a bad deck, and two potential underlying causes are put forward. The first one is that deck B is very similar to decks C and D in terms of net losses calculated for each trial, as opposed to deck A; decks B, C and D all yield either no or very few net losses, while deck A yields frequent and large net losses. Deck B thus might be too similar to decks C and D in terms of net outcomes (see (Lin et al., 2007) for a detailed explanation). The second potential cause is that, for each deck, losses vary across trials while immediate rewards do not and are completely predictable. This could result in participants focusing more on immediate losses to adapt their decision strategy rather than long-term gains, thereby favoring deck B which is more predictable than deck C and yields greater immediate gains than deck D. In the present study, it is possible that this “deck B phenomenon” was responsible for some participants’ poor performance, since deck B was chosen relatively frequently in the second half of the task, as shown in Figure 6. However, it does not explain why deck A was also selected frequently in later trials, while A is considered to be the most obvious choice to avoid (Steingroever et al., 2013).

While a lack of motivation has been proposed as another possible explanation for poor performance in healthy participants, (Fernie & Tunney, 2006) have shown that increasing motivation by using real money instead of facsimile money did not lead to better performance across the board. Instead, they found that healthy participants improved when they were given more information about the task in the instructions (e.g. some decks are better than others). Therefore, while motivation does not seem to explain the poor performance of healthy individuals, the difficulty of the task probably does, and the amount of information provided in the instructions is more important than previously thought. Since our version of the IGT employed the same instructions as the original one, which contain relatively little information, it is possible that the difficulty of the task (when no additional information is provided) is what was responsible for the poor performance of certain participants.

Another possible explanation for poor performance in healthy individuals is that the number of trials could be too low and insufficient to learn about the particularities of each deck. (Wetzels et al., 2010) showed that healthy participants are actually able to learn to prefer the good decks over the bad decks, but that they require at least 100 trials to do so. Their reasoning behind this slow learning process is that the frequency of losses in decks B and D is too low (i.e. once in 10 cards), which provides too little information about those decks to quickly learn to avoid deck B. In the present study, this conjecture could also explain the unusually high preference for deck B compared to deck D in later trials (see Figure 6), especially considering that we had to cut down the number of trials from the original 100 to 75.

Finally, (Caroselli et al., 2006) studied the IGT paradigm applied to young and healthy university students and, similarly to the present study, observed an overall preference for the decks considered to be disadvantageous by (Bechara et al., 1994) (i.e. decks A and B). They even noted that the card selection preferences of their undergraduates were more similar to those of (Bechara et al., 1994)'s frontal-lobe-damage patients than to those of their healthy controls. In addition, their analysis highlighted a "frequency-of-reinforcement" effect, by which participants chose decks B and D more often than A and C simply because they yield a net gain on 90% of trials compared to 50% for the latter two, regardless of whether decks were advantageous or disadvantageous in the long term. Moreover, since it has been shown that 1) IGT choices that offer larger immediate rewards or losses were associated with stronger anticipatory skin conductance responses (SCRs) irrespective of long-term consequences (Tomb et al., 2002), and that 2) high SCRs, in some circumstances, may indicate approach behavior rather than avoidance behavior (Damasio et al., 2002), (Caroselli et al., 2006) posited that university students could be particularly aroused by the higher stakes associated with decks A and B, and could thus favor them over the long term benefits of the advantageous decks. Therefore, according to the authors, it is likely the interaction between the aforementioned frequency-of-reinforcement effect and this physiological arousal effect that led university students to prefer deck B, creating another "deck B phenomenon" resembling what (Steingroever et al., 2013) observed. In addition, the arousal effect associated with decks A and B could explain why our participants showed a disproportionate preference for those decks. (Caroselli et al., 2006) also point out the importance of the complexity and relative "open-endedness" of the paradigm. They speculate that these characteristics of the task, combined with a low level of information in the instructions, could lead to a disregard of the instructions, in which case participants who perform poorly could simply be disregarding the instructions and playing to maximize the number of net gains.

Our unusual IGT performance results were presumably the by-product of a combination of many of the possible explanations presented above, which all challenge basic assumptions of the task and its validity as a research tool when used to measure risk preference.

The Iowa Gambling Task was selected for this experiment in part because it has been shown to be associated with self-reports and observations of risky driving behavior. However, when such links were observed, a tendency to learn to choose more advantageous decks was observed in most participants; these studies had participants that showed significant improvement in choosing more advantageous decks over the course of the task. As made clear by our own results as well as most studies referenced in this section, healthy participants often fail to learn to choose the more advantageous decks over time, which calls into question the validity of the IGT score as a measure of risk preference. We believe that the lack of learning from many of our participants during the IGT prevented us from obtaining accurate objective assessments of risk preference from this task, and could potentially explain why no significant associations were found between IGT-derived risk preference and both driving behavior and brain activity. Because the present study failed to do so, it has yet to be determined whether the Iowa Gambling Task, when correctly understood by participants, has predictive validity with respect to objective measures of risky driving.

Nonetheless, it is worth noting that our results are consistent with those from (Le Bas et al., 2015)**,** who did not find any link between IGT selections and self-reported risky driving. However, in their study, all IGT trials were included in the score calculation, and learning was not accounted for. It is thus not clear whether their subjects were able to learn the contingencies of the task and if that could have explained their result.

2.5.2 Balloon Analogue Risk Task

The BART, as opposed to the IGT, appears to have been well understood and executed by all participants; performance results showed that, in our sample, the average number of adjusted pumps and its variability are typical of what has been observed in previous studies with healthy participants (C. W. Lejuez et al., 2003; Xu et al., 2013). Therefore, the validity of this BART score as a risk preference index cannot be as easily questioned as the IGT’s.

Nonetheless, no association was found between the BART score and risky driving during the simulation. This result is consistent with that of (Gordon, 2007) and (Le Bas et al., 2015), who found that performance on the BART did not predict self-reports of risky driving, but not with the numerous studies that did observe a link between BART performance and self-reports of risky driving (Ba, Zhang, Peng, et al., 2016; Cheng et al., 2012; Piccardi et al., 2021; Vaca et al., 2013).

The main strength of the BART is its ecological validity, which is supported by numerous studies that found a positive association between the average number of adjusted pumps and reports of substance abuse and general risk-taking behaviors (Aklin et al., 2005; Fernie et al., 2010; Hopko et al., 2006; C. Lejuez et al., 2003; C. W. Lejuez et al., 2002, 2003; Mishra et al., 2010). The task has also been shown to have good test-retest reliability (White et al., 2008), and was linked to scores on risk-related constructs (i.e. sensation seeking and impulsivity)(C. W. Lejuez et al., 2002).

However, the BART has more recently received notable criticism by researchers who consider the task's ability to measure risk preference limited by design (De Groot, 2020; Groot, 2018; Gu et al., 2018; Schmidt et al., 2019; Schonberg et al., 2011). The issues pointed out by those researchers concern three specific characteristics of the task.

First, the BART comprises uncertainty in addition to risk. Because participants are not given "detailed information about the probability of an explosion" (as per the original instructions from (C. W. Lejuez et al., 2002)), it can be assumed that, at least during early trials, participants make their decisions under uncertainty rather than risk (Groot, 2018). That alone raises concern as uncertain and risky decisions involve different mental processes (Volz & Gigerenzer, 2012). Moreover, similarly to the IGT, as participants observe the outcomes of early trials in the BART, they develop a better sense of the probabilities of the task, and gradually make decisions under more risk than uncertainty as the task progresses. This shift from uncertain to risky decisions entails a process of learning the task probabilities based on experience in previous trials—a type of learning that has been shown to lead to different decisions than learning from a description (Rakow & Newell, 2010). The main issue with all of the above is that it is in fact impossible to determine which trials happened under uncertainty, experience-based risk or description-based risk for reasons expanded upon by (De Groot, 2020). As a result, BART scores calculated over the whole task (which is typically the case) are not only influenced by risk preference, but also one's attitude towards uncertainty, the ability to update one's knowledge of the probabilities and the ability to remember previous events. In the context of measuring preference for risk, the same criticism applies to the IGT as well, as it requires similar experience-based learning of probabilities (Groot, 2018).

Second, the BART's design censors high risk preference, and thus skews scores downwards. When a balloon explodes, the trial ends and is excluded from any analysis based on the average number of adjusted pumps, which is the recommended metric for this task (C. W. Lejuez et al., 2002).

Therefore, the more risk someone is willing to take, the more likely it is that balloons burst (simply because they will pump them more), and that high-risk trials are excluded from data analysis. In such a case, an individual's high preference for risk would not be fully reflected in their score which would be biased downwards (De Groot, 2020).

Third, the BART confounds risk with expected value. The task's structure is made so that, within a trial, both the balloon value (the amount of points/money accumulated in the temporary bank) and the probability of explosion increase with every pump. Therefore, a balloon's expected value changes across a trial (Schmidt et al., 2019). As a result, both risk and expected value may influence the decisions of participants during the BART, which limits its ability to measure risk preference (De Groot, 2020).

In sum, certain researchers have recently argued that, for the above reasons, the typical metric derived from the BART (the number of adjusted pumps averaged over the whole task) cannot be interpreted as a straight-forward measure of risk preference. While supposedly assessing a single cognitive construct (risk preference), the task manipulates other, potentially confounding constructs (e.g. uncertainty and expected value), in addition to having a bias against risk takers (De Groot, 2020). It is thus possible that the BART did not allow us to accurately measure risk preference in our sample, which could explain the lack of association between task performance and risky driving behavior in the simulation. Along with the research cited in (De Groot, 2020), our results highlight the need for more research on what the BART actually measures, and on its ability to predict naturalistic risky behavior in a controlled environment.

2.5.3 Domain-Specific Risk-Taking scale

The global score from the DOSPERT scale was significantly associated with higher speed as well as more steering in the track's curves, which were both operationalized as risky driving behavior. These associations corroborate a recent finding that risk-prone individuals—assessed using the DOSPERT—took more risks during a motorcycle simulation that consisted of urban road scenarios (Baltruschat et al., 2020). They are also consistent with studies that found a link between DOSPERT scores and self-reports of risky driving (Padilla et al., 2018; Sween et al., 2017).

Together, these results suggest that the DOSPERT scale as a whole has predictive validity with respect to risky driving behavior.

However, this predictive validity remains limited by a lack of neurophysiological support; the global DOSPERT score was not significantly associated with driving brain activity specific to decision making under risk. While neurophysiological correlates of DOSPERT scores have been captured in various contexts (Azanova et al., 2021; Barkley-Levenson et al., 2013; Lee & Jeong, 2013; Lee & Young Park, 2011), these studies had their participants remain mostly still (either in resting state or immobilized in a scanner). The present study's driving simulation required participants to regularly make both fast and slow movements with their head and limbs, which can generate artifacts to EEG signals that can be challenging to manage. Despite such difficulties, many studies have successfully identified patterns of brain activity while subjects were moving substantially by employing advanced artifact correction methods such as independent component analysis (ICA), canonical correlation analysis (CCA) and the wavelet transform (Urigüen & Garcia-Zapirain, 2015).

While it is possible that, in the present study, movement artifacts and/or their filtering interfered enough with the signals of interest to blur detectable neural correlates of risk preference, the EEG data normalization could also have been responsible for producing signals that lack features associated with the psychological trait. The normalization of high DMUR data with low DMUR data was performed to isolate brain signals specific to the process of decision making under risk that occurred over certain parts of the track. It is however possible that, in doing so, cortical signals resulting from cognitive processes associated with preference for risk were canceled out. This normalization method should thus be further tested for its ability to isolate neurophysiological signals that embody complex psychological traits such as risk preference.

The ethical DOSPERT score was associated with higher engine speed in the curves. This telemetry variable (engine speed in the curves) was included in the analysis because a high value is indicative of aggressive driving that, in most cases, significantly increases the risk of accident due to the high longitudinal acceleration (and thus speed) it is usually associated with. However, the significance of this result is not clear-cut for three reasons. First, the association only involves one out of the four risky driving variables, and excludes both longitudinal speed and lateral acceleration, which suggests that the level of risk incurred in the curves by participants prone to ethical risk was not particularly high compared to those prone to risk in general (i.e. with a high global DOSPERT score). Second, the predictive validity of the ethical subscale observed here loses plausibility to the fact that risky driving alone on a race track hardly involves any ethical consideration. Third, an alternative explanation could be that participants prone to ethical risk did not care as much about task objectives and had a tendency to mindlessly floor the throttle during curves, which very few would attempt with a real car. It is thus unlikely that the association between ethical risk preference and risky driving behavior would generalize to instances of real-world driving.

A higher score on the recreational DOSPERT subscale was associated with increased normalized high DMUR brain activity in the theta, alpha and beta frequency ranges in various brain regions (see Table 5 and Figure 9). Most notably, a higher recreational risk preference was associated with higher normalized high DMUR theta activity over the left occipital cortex; alpha activity over the bilateral occipital, right parietal and right temporal cortices; and beta activity over the occipital and parietal cortices of the right hemisphere. However, since recreational risk preference was not associated with risky driving behavior in the simulation, these neurophysiological correlates of the recreational DOSPERT score are likely to be unrelated to the predictive validity of this score with respect to risky driving behavior.

Lastly, a higher social DOSPERT score was associated with increased normalized high DMUR beta activity over the bilateral middle and inferior frontal gyri, the bilateral pre- and postcentral gyri, and the left superior temporal gyrus. Electrophysiological studies on humans and monkeys generally confirmed the idea that beta rhythm is associated with preparation and inhibitory control in the motor system: beta power is decreased at the onset of movement execution and increased when a response is withheld (Wang, 2010). Beta power has also been associated with high cognitive task demands and higher neurophysiological function (Baumeister et al., 2008). Nonetheless, since social risk preference was not associated with risky driving behavior in the simulation, these neurophysiological correlates of the social DOSPERT score are likely to be unrelated to the predictive validity of this score with respect to risky driving behavior.

It is also worth noting that the DOSPERT scale items that involve risky driving are part of the health/safety domain of risk taking (Blais & Weber, 2006), the score of which should thus be expected to have predictive validity with respect to risky driving behavior. However, this association was not expected in this experiment because participants drove without there being any risk for their health or safety. For many studies of risk-taking that simulate real-life conditions that do involve safety risks (such as this one), this ethical requirement can unfortunately limit the extent to which natural levels of risk preference are expressed in a laboratory environment, and, to our knowledge, nothing can be done to compensate for this shortcoming.

2.5.4 Limitations

One evident limit of this study is the size of the sample used; a sample of 18 university students with valid driving licenses might be too small and narrow to allow generalization of the present findings to the much larger population of drivers of all ages and socioeconomic backgrounds. In addition, it is possible that our sample size led to a statistical power that was sufficient to reveal associations such as between the DOSPERT and risky driving behavior, but insufficient to reveal the more subtle neurophysiological evidence supporting this association as well as potential trends such as between BART performance, risky driving and brain activity.

A second limit of this experiment is the fact that participants completed a total of three different risk-taking tasks in the same session (i.e. IGT, BART & driving task), while a reward was only directly associated with the last one of them. It seems possible that motivation to perform well on these tasks was thus not constant throughout the experimental session, and that certain participants put a different level of effort toward each task, thereby potentially blurring associations of interest. A reward was only tied to performance in the driving task due to limited funds and to the decision to prioritize motivation for this task, which was made because the driving task is not standardized and allows a broad range of behavior that does not involve risk (e.g. driving mindlessly around the track because it is fun). Future studies that employ multiple risk-taking tasks should therefore pay particular attention to how the experimental design accounts for motivation levels throughout the experiment.

The driving simulation task also presents an important limitation in terms of the behavior it promoted. The task objectives and the associated reward encouraged participants to drive fast around the track to improve their lap times and gain additional compensation. While the task was designed this way to bring about risky driving on the track, it also possibly limited the natural expression of risk preference to some extent. By encouraging all participants to essentially drive as fast as possible to complete the objectives, the sample's natural variability in the tendency to drive fast might have been constrained. Participants who normally never take risks at the wheel might have felt pressured to take more risks than their natural risk preference would normally lead them to. As a result, the range of risky driving behavior exhibited on the race track might have been constrained and particularly biased toward more risk taking. This phenomenon could be related to the lack of association between BART performance and risky driving behavior in this experiment. Future driving simulation studies of risk preference should thus adapt their driving task so that its design, context and objectives generate less incentive to take risks and leave more room for the expression of the full natural range of risk preference, as measured by the DOSPERT scale.

2.5.5 Implications & future work

This study indicates that the global DOSPERT score—a subjective measure of risk preference—has predictive validity with respect to risky driving behavior in a simulator, but that BART performance—an objective measure of the same trait—does not. A possible implication of these results is that risk preference instruments based on self-reports do not measure the same components of risk taking as those based on objective assessments, and that the components they measure more closely mirror those involved in risky driving. The idea that different risk preference instruments measure different components of risky behavior has already been put forward by many researchers (Frey et al., 2017; Hertwig et al., 2019; Mata et al., 2018; Mishra & Lalumière, 2011). Of particular interest is one study from (Mishra & Lalumière, 2011), who found that the DOSPERT was strongly associated with the risky personality component of risk taking, while the BART was much more associated with variance preference. Here, risky personality refers to personality traits associated with risk taking, while variance preference refers to a preference for choices that present ambiguous probability information, which people tend to associate with a high outcome variance (Rode et al., 1999). The present study's driving task involved risky motor decisions associated with fast driving around the track (e.g. braking or turning the wheel at a specific moment). These decisions can be influenced by a risky personality, because the associated traits such as high impulsivity, high sensation-seeking and low self-control can evidently lead one to take more risks in a task that involves driving fast for a potential reward. However, this study's driving task did not comprise choices with particularly ambiguous probability information; for the vast majority of the risky motor decisions required, the probability information associated with each decision's outcome was hardly ambiguous, because participants were used to driving the car (and cars in general) and were thus intuitively aware of the possible outcomes of their risky motor decisions, i.e., either the car keeps its adherence to the road and keeps moving in the intended direction, or adherence is lost, the car drifts, and control is lost to some extent. Our study's results are thus consistent with the aforementioned findings from (Mishra & Lalumière, 2011); the BART score, which they found to be related to variance preference, did not predict risky driving in a task in which risk-taking is not (or very weakly) associated with variance preference, while the global DOSPERT score, which they found to be related to a risky personality, did predict risky driving in a task in which risk-taking is associated with a risky personality. Together, these results suggest that risk preference instruments based on self-reports have more predictive validity with respect to risky driving than those based on objective assessments. A natural progression of this work would be to confirm or disprove this idea. The present study should thus be repeated with the main goal of comparing these two types of risk preference instruments, both in terms of their predictive validity with respect to risky driving and in terms of the neurophysiological correlates of their scores in a driving context. In addition, as mentioned previously, the IGT should be included in such a study, its instructions should be modified to ascertain an adequate understanding of the tasks by all subjects, and motivation levels across the entire experimental session should be properly maintained or controlled for.

The results of this study also have practical implications. The finding that the global DOSPERT score was associated with risky driving is promising for organizations interested in predicting and/or preventing instances of risky driving. In addition to public safety agencies, a notable example is that of insurance companies; the predictive validity of measurable psychological factors associated with risky driving behaviors such as distracted driving could be highly useful to car insurers, who could then adapt their services based on predictions of the likelihood of insured customers to carry out undesirable behavior. While they already adapt their services based on personal characteristics such as past driving record, location, age and car driven, to our knowledge, insurance companies do not consider psychological traits that are not the result of a mental disorder in the appraisal of customers seeking insurance. Ethical considerations aside, car insurers could thus greatly benefit from tools—such as the DOSPERT scale—that could provide objective measures with predictive validity regarding their customers' driving behavior. However, for this application to be realistically possible, this predictive validity should be objectively shown to generalize to driving in the real world. To investigate this possibility, a similar study could be repeated in a context closer to real-world driving, which should at least include the presence of other cars and a driving environment that simulates public roads instead of a race track.

Finally, the lack of neurophysiological evidence for the association between the DOSPERT score and risky driving behavior in this study emphasizes the need for more research on the neural correlates of risk preference in ecologically valid contexts, how they could be integrated to current theories of decision making under risk, and how they might explain the low predictive validity of certain risk preference measures with respect to risky driving in a laboratory environment. Importantly, future investigations with this neurophysiological focus should invest a great deal of effort toward handling muscle artifacts in EEG signals, which tend to become increasingly complex as the experimental conditions become closer to the real world.

2.6 Conclusion

The present study investigated the relationship between risk preference—as measured through different means—and risky driving in a simulator, as well as the associated oscillatory brain activity. The DOSPERT scale's global score was found to be significantly associated with risky driving behavior in the risky portions of the simulation, while the scores of individual DOSPERT subscales were not. However, no links were found between performance on the risk-taking tasks (the IGT and the BART) and risky driving behavior. The EEG analysis also did not reveal significant oscillatory neural correlates of risk preference in the driving task.

The main theoretical implication of this research is that risk preference instruments based on self-reports appear to differ from those based on objective assessments in the risk-taking components that they measure—as has been suggested in the literature. Results from the driving simulation support the idea that the DOSPERT scale is more strongly associated with risk attitudes such as those involved in driving than the BART, which has been associated with variance preference

(Mishra & Lalumière, 2011) and shown to comprise several methodological problems when used to measure risk preference (De Groot, 2020).

This study also has practical implications; the observed predictive validity of the DOSPERT scale to risky driving is evidence that the prediction and prevention of risky driving in the population could be facilitated by the use of risk preference instruments based on self-reports of risk attitudes, a finding from which organizations such as public safety agencies and insurance companies could benefit from. Moreover, the lack of neurophysiological evidence in this study despite the methodological efforts deployed exposes some of the challenges associated with isolating neural correlates of complex psychological traits such as risk preference in naturalistic contexts, especially those involving movement.

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Chapitre 3: Conclusion

3.1 Rappel des questions de recherche et principaux résultats

Le principal objectif de ce mémoire était d'évaluer dans quelle mesure il est possible de prédire la prise de risque au volant dans une simulation de conduite à l'aide de différentes mesures de propension au risque. Le deuxième objectif avait comme but de potentiellement supporter de façon théorique les résultats du premier grâce à la neurophysiologie. Il consistait à déterminer dans quelle mesure il est possible de prédire l'activité cérébrale oscillatoire reliée à la prise de risque au volant dans une simulation de conduite à l'aide des mêmes mesures de propension au risque.

Pour répondre à ces objectifs, une étude en laboratoire a été effectuée auprès de 18 participants qui ont complété deux tâches permettant de mesurer la propension au risque (la *Balloon Analogue Risk Task* [BART] et la *Iowa Gambling Task* [IGT]), un questionnaire mesurant le même construit (l'échelle *Domain-Specific Risk Taking* [DOSPERT]), ainsi qu'une tâche de simulation de conduite dans laquelle la prise de risque fut mesurée de façon objective. L'électroencéphalographie fut employée pour capturer l'activité cérébrale oscillatoire des participants pendant certains moments risqués de la simulation.

Les résultats de l'analyse comportementale démontrent que seulement le score global de l'échelle DOSPERT a eu un pouvoir prédictif pour la prise de risque pendant la simulation, soit pour la haute vitesse et les virages brusques. Les scores aux dimensions individuelles de l'échelle DOSPERT ainsi que les scores aux tâches BART et IGT n'ont pas dévoilé d'associations avec la prise de risque au volant. L'analyse des données neurophysiologiques n'a révélé aucune association entre les scores aux différentes mesures de propension au risque et l'activité cérébrale oscillatoire des participants pendant les moments risqués de la simulation.

Les résultats de cette étude suggèrent principalement que des mesures de la propension au risque prenant la forme de questionnaire (donc des mesures subjectives et autodéclarées) ont plus de potentiel prédictif pour la prise de risque au volant que des mesures objectives prenant la forme de tâche interactive.

3.2 Contributions de l'étude

Cette étude permet d'éclaircir davantage les déterminants psychologiques de la prise de risque au volant en démontrant que ceux capturés par une mesure subjective de la propension au risque sont plus significativement associés à ce comportement que ceux capturés par deux mesures objectives du même construit. Plus spécifiquement, les composantes psychologiques que capture l'échelle DOSPERT dans son ensemble semblent être d'importants déterminants de la prise de risque au volant. La section 2.5.5 de ce mémoire explique en détail comment cette idée s'inscrit dans la littérature sur la prise de risque et la propension au risque.

D'un point de vue méthodologique, cette étude souligne le défi que représente la capture de corrélats neurophysiologiques d'un comportement complexe comme la prise de risque au volant. Ce comportement implique une multitude de processus cognitifs et requiert des mouvements importants—deux éléments qui compliquent de façon significative une analyse neurophysiologique telle qu'effectuée dans ce mémoire.

Dans un contexte de prédiction de la prise de risque au volant, les résultats de cette étude suggèrent qu'un outil de mesure simple tel qu'un questionnaire sur la propension au risque dans différents domaines possède une valeur prédictive significative. Une compagnie d'assurance automobile désirant estimer la probabilité que ses clients soient impliqués dans un accident pourrait donc tirer profit de cette valeur prédictive. Par exemple, puisque la plupart de ces compagnies emploient déjà une application mobile utilisée par leurs clients, l'intégration d'un simple questionnaire à celle-ci serait envisageable. Pour les clients réticents au concept de l'assurance télématique, cette approche pourrait être une alternative intéressante, alors que pour les programmes d'assurance télématique déjà en vigueur, cette approche pourrait représenter un complément intéressant pouvant augmenter la capacité d'estimation du potentiel de risque des clients assurés. L'avantage d'un questionnaire comme l'échelle DOSPERT est que c'est un outil de mesure facile à implémenter et peu coûteux comparé à une tâche interactive. De plus, les instructions d'un questionnaire sont faciles à comprendre comparées à celles de certaines tâches comme la IGT (voir section 2.5.1 pour plus de détails).

Finalement, la valeur prédictive de l'échelle DOSPERT pour la prise de risque au volant pourrait également servir des agences de sécurité publique, qui pourraient employer un tel questionnaire pour cibler les individus plus enclins à prendre des risques sur la route et ainsi mieux mobiliser leurs efforts de sensibilisation.

3.3 Limites et pistes de recherches futures

Bien que cette recherche ait décelé un potentiel prédictif de l'échelle DOSPERT pour la prise de risque au volant, certaines limites pourraient avoir restreint la portée des résultats obtenus.

D'abord, l'échantillon de participants était constitué de 18 jeunes universitaires; il est donc possible que nos résultats ne se généralisent pas à l'ensemble de la population de conducteurs. Il serait donc souhaitable d'effectuer une étude similaire avec un échantillon plus volumineux et plus représentatif de la population dans son ensemble.

De plus, la tâche de conduite développée pour cette expérience a été conçue de sorte à ce qu'elle encourage la prise de risque tout en étant assez simple pour permettre d'isoler des moments clés durant lesquels la prise de risque a lieu (si un participant décide bel et bien de prendre des risques). Cependant, il est possible que, en encourageant la prise de risque, nous ayons limité l'expression naturelle de la propension au risque sur la route, et que la simplicité de la simulation de conduite ait limité la généralisation des résultats à une conduite impliquant d'autres automobiles et un code de la route à respecter. Il serait donc pertinent de reproduire une étude similaire avec une tâche de conduite dont les objectifs laissent davantage place à l'expression naturelle de la propension au risque au volant, et dont les conditions reflètent davantage celles qu'on retrouve sur les routes.

Finalement, puisque cette étude suggère que les mesures subjectives de la propension au risque sont de meilleurs candidats pour la prédiction du risque au volant que les mesures objectives, il serait intéressant d'étudier le potentiel prédictif d'autres questionnaires mesurant la propension au risque en général, ainsi que de plusieurs combinaisons de ce type de questionnaire.

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Annexes

Annexe 1. Affiche présentée à la conférence annuelle de *Society for Neuroeconomics* en 2020